EVALUATION OF SECTION 1109 OF THE AFFORDABLE CARE ACT: ADDITIONAL MEDICARE FUNDING TO HOSPITALS LOCATED IN LOW MEDICARE SPENDING COUNTIES

By

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The views expressed within this paper are attributed to Nisha Bhat and not the Centers for Medicare and Medicaid Services

Abstract

Objective

This study examines the implementation of Section 1109 of the Affordable Care Act (ACA) that provided additional funding to hospitals located in counties with low Medicare per beneficiary spending, as a way to address geographic variation in Medicare reimbursement to hospitals. This study seeks to determine: 1) whether the hospitals that benefitted from this provision show any differences in the quality of care compared to hospitals that did not benefit from this provision, 2) t if the hospitals that benefitted from this provision showed improvement in quality of care after receiving the additional compensation and 3) whether there is a relationship between the amount of money a Section 1109 hospital received and the change in quality of care. Improvement in quality of care is measured by changes in the 30-day hospital readmission rates and mortality rates for Medicare patients with acute myocardial infarction (AMI), pneumonia and heart failure.

This study seeks to add to the literature on whether there is a relationship between Medicare spending and quality of care and whether giving hospitals more reimbursement improves quality of care.

Methods

The study evaluates the three hypotheses using bivariate analyses, multivariate linear regression models, difference-in-difference models and propensity scores to compare performance on the quality of care indicators for Section 1109 hospitals and the comparison hospitals. The study uses Medicare quality of care measures and payment data based on Medicare claims.

Results

The results show that prior to receiving the additional funding, Section 1109 hospitals are different from non-Section 1109 hospitals with respect to the quality of care provided. Section

1109 hospitals had statistically significant higher (or worse) 30-day Medicare FFS mortality rates and statistically significant lower (or better) 30-day Medicare FFS readmission rates for AMI, pneumonia and heart failure compared to non-Section 1109 hospitals. However, after the Section 1109 hospitals received their additional funding, there were no statistically significant differences in the change in quality of care for Section 1109 hospitals as compared to non-Section 1109 hospitals. Also, there was no relationship on the amount of money that Section 1109 hospitals received and the change in quality of care.

Conclusion

These results can inform policymakers that Medicare paying more money to hospitals does not necessarily mean that patients will receive better quality of care.

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Glossary

ACA= Affordable Care Act

ACO= Accountable Care Organization

AMI = Acute Myocardial Infarction

CMS = Centers for Medicare and Medicaid Services

DRG= Diagnosis Related Group

DSH= Disproportionate Share Hospital

ED = Emergency Department

EHR = Electronic Health Record

EP= Eligible Professional

ESRD = End Stage Renal Disease

FFS = Fee for Service

FY = Fiscal Year

HAC = Hospital Acquired Condition

HCAHPS = Hospital Consumer Assessment of Healthcare Providers and Systems

HCC = Hierarchical Condition Categories

HF = Heart Failure

HQA = Hospital Quality Alliance

HRR = Health Referral Region

HSA = Health Service Area

IME= Indirect Medical Education

IOM = Institute of Medicine

IPPS= Inpatient Prospective Payment System

MACRA = Medicare Access and CHIP Reauthorization Act of 2015

MDH = Medicare Dependent Hospital

MIPS = Merit-based Incentive Payment System

MSA = Metropolitan Statistical Area

MS-DRG = Medicare Severity- Diagnosis Related Group

OPPS = Outpatient Prospective Payment System

P4P = Pay for Performance

PN = Pneumonia

SCH = Sole Community Hospital

SGR = Sustainable Growth Rate

Chapter 1: Introduction

Overview

The Affordable Care Act that was enacted in March 2010 made numerous changes to the U.S health care system and was the largest piece of health care legislation enacted since the initial enactment of Medicare in 1965. While the Affordable Care Act is largely known for aiming to provide near-universal access to affordable health coverage, it also sought to reform most aspects of the health care delivery system including private insurance coverage, the Medicaid program and the Medicare program. The Affordable Care Act promulgated both short term and long term changes in the Medicare program in terms of coverage and reimbursement and it sought to create Medicare payment reform. During the development of the ACA, one area of contention in the Medicare hospital reimbursement program was the geographic variation in per capita Medicare spending wherein hospital reimbursement varied across the country for the same set of hospital services. Policymakers and researchers also showed that in addition to variation in reimbursement, there was unexplained variation in utilization and the types of cases treated across the country. There has been much research done to understand potential causes for the geographic variation of Medicare utilization and spending. Geographic variation in Medicare spending is also a politicized issue because the Medicare program annually sets hospital payment rates under the Inpatient Prospective Payment System (IPPS) and Outpatient Prospective Payment System under a budget neutral model, to ensure that changes to the payment systems do not increase spending beyond a certain percentage each year. Because there is theoretically a fixed amount of money, there is a tension where hospitals seek to maximize their Medicare revenue and obtain the largest proportion of that pool of dollars.

Under the Affordable Care Act, there were several provisions to evaluate geographic variation in Medicare spending, including provisions for CMS to submit a Report to Congress which could be followed by Congress acting to address geographic variation. However, the Affordable Care Act did not contain many provisions to make immediate changes to the Medicare payment systems to account for geographic variation and those hospitals that were perceived to be under-reimbursed under the Medicare payment systems continued to complain. There was a last minute inclusion of Section 1109 of the Affordable Care Act that sought to provide $400 million to hospitals located in the bottom quartile of counties with the lowest Medicare per beneficiary spending, adjusted for age, sex and race, as a short-term mechanism to address geographic variation.

In 2010, CMS calculated county-level Medicare per beneficiary spending adjusted for age, sex and race and identified hospitals located in those counties with the lowest Medicare spending per beneficiary. Consistent with the law, CMS determined how to apportion the allotted funding to those hospitals in 2011 and 2012. Approximately 400 hospitals received money under this provision. However, the distribution of the money surprised the hospital community because it was expected that much of the money would be distributed to so-called low cost or "efficient" parts of the country like Iowa or Minnesota, but rather the money was distributed to states known for their large metropolitan areas, but also having significant rural areas including Virginia and New York.

The intent of the provision was to provide a bonus payment to hospitals located in areas with low per capita Medicare spending as a means to provide extra Medicare reimbursement. This study evaluates the results of the provision, examining the impact to the hospitals that received the money. The goal of the study is to assess whether the hospitals that benefitted from this provision have any differences in the health outcomes of their patients with respect to 30-day readmission rates and 30- day mortality rates as compared to the hospitals that did not benefit from this provision. In addition, this study explores whether these hospitals have any differences in improvement in quality of care after receiving the funds under Section 1109. Ultimately, this study seeks to assess whether if Medicare pays hospitals more money, do patients receive better quality of care.

Overview of the Medicare Inpatient Prospective Payment System

As background, Medicare reimburses acute care hospitals for providing inpatient acute care services to Medicare beneficiaries under the Inpatient Prospective Payment System (IPPS). The IPPS was a major departure from Medicare's previous system, which reimbursed according to a cost-based system. Under the IPPS, hospitals receive a payment on a per case basis for Medicare inpatient stays. The payment is no longer based on the length of stay or the cost of the stay. Rather, payment for each inpatient stay is based on the patient's diagnosis and the national average cost of the resources used to treat patients with a similar illness.

Under this fee-for-service prospective payment system, Medicare sets the payment rates annually in advance of each year and determines the payments on a per-procedure basis. In general, discharges are assigned a diagnosis-related group (DRG), which is a classification system that groups similar clinical conditions or diagnoses and procedures. A patient's principal diagnosis and up to 24 secondary diagnoses that reflect a patient's comorbidities and complications and procedures determine the DRG assignment of the case.

Since October 2007, Medicare uses a DRG classification system known as Medicare Severity DRGs (MS-DRGs) that were developed to better account for severity of illness and resource consumption based on severity. As such, there are three levels of severity for an MS-

DRG, including a "major complication/comorbidity", "complication/comorbidity" and "non-complication/comorbidity". Each MS-DRG is assigned a relative weight that reflects the average relative costliness for the average Medicare case. The MS-DRG base relative weight of 1.0 signifies the cost of the services provided to the average Medicare patient. Illnesses that are more costly or more resource intensive receive higher relative weight values and illnesses with less costs or resource use receive lower relative weight values.

The other component of the IPPS payment is the standardized amount, or payment rate to which the DRG relative weight is applied. Medicare reimburses through two payment rates- one payment rate to cover operating costs and another payment rate to cover capital costs. A portion of the operating payment rate is adjusted by an area wage index value that reflects differences in labor market prices and differences in hospital wage rates. Hospitals located in labor market areas with higher wages than the national average wage will have their payment rate upwardly adjusted while hospitals located in labor market areas with wages lower than the national average will have their payment rate downwardly adjusted. There are also rules that allow for hospitals to "reclassify" and receive a wage index for another labor market area. The wage index, which is based on differences in geographic labor market variation contributes to geographic variation in Medicare prices and spending.

Finally, there are several policy payment adjustments that affect the IPPS payment. Teaching hospitals, or hospitals that train residents, receive an additional per-case indirect medical education (IME) payment, which reflects the indirect patient care costs of teaching hospitals relative to non-teaching hospitals. In addition, hospitals that treat a disproportionate share of low-income patients receive additional reimbursement called a Medicare Disproportionate Share Hospital (DSH) payment, and more recently under the Affordable Care

Act, hospitals receive an additional payment based on their relative uncompensated care costs, on each inpatient claim payment. For cases in which the inpatient is transferred to another hospital, the originally admitting hospital receives a reduced payment. Outlier cases, i.e. cases that are extraordinarily costly, get a higher Medicare IPPS payment. For high cost new technologies that provide a substantial clinical improvement over existing treatments, an additional payment is provided to discharges that utilize that new technology.

In more recent years, there are special payment adjustments to the IPPS established for hospitals in rural areas, in order to preserve access to care in those areas. Hospitals that are classified as rural can further be designated for special payments. Sole Community Hospitals (SCHs) are in a rural area that are a certain distance from other hospitals, and can be paid the higher of either the IPPS payment or a hospital-specific cost-based rate. Medicare Dependent Hospitals (MDHs) receive additional payments which are intended for small rural hospitals for which Medicare patients make up a significant percentage of inpatient days or discharges. Lastly, hospitals that are 25 miles (FY 2011 through 2017 it was 15 miles) from another hospital and with few Medicare discharges can receive a low volume payment which is a percentage add-on of their total IPPS operating payment.

In addition to the IPPS operating payment, Medicare also provides for an IPPS capital payment that is intended to reimburse for fixed capital costs for a hospital. The capital payment is similarly adjusted by the wage index, and teaching hospitals and hospitals that serve a greater share of low-income patients can receive an additional amount under their capital payment.

Under the Affordable Care Act, there have been several payment polices that affect a hospital's IPPS payment based on certain quality of care measures. The Affordable Care Act established the Hospital Value Based Purchasing Payment Program, effective in 2012, which is a redistributive payment policy, in which hospitals can receive bonus payments or payment reductions based on their performance on a composite score of measures, including patient satisfaction, 30-day mortality rates and Medicare spending per beneficiary. The Affordable Care Act also established the Hospital Readmissions Reduction Program, effective beginning in October 2012, which reduces hospital payments for poor performance on 30-day readmissions for pneumonia, heart failure and AMI. Under the Hospital Readmissions Reduction Program, a hospital is evaluated for its performance during a three- year historical period and if the hospital's performance on readmissions for a particular condition is worse than the national average, all of the hospital's discharges for the upcoming year will receive a reduction in payments. For both the Hospital Readmissions Reduction Program and the Hospital Value Based Purchasing Program, the payment adjustment is applied to the hospital's base operating DRG amount, or wage-adjusted DRG payment so add-on payments like DSH or IME are not affected. Lastly, beginning in October 2014, hospitals ranked in the worst performing quartile for hospital-acquired conditions are subject to a one-percent penalty on their entire inpatient hospital payment.

Example Formula of IPPS Operating Payment

IPPS Operating DRG Payment= [(Wage Index x Labor Related Standardized Amount + Non Labor Related Standardized Amount) x DRG Weight]

Total IPPS operating payment= Operating DRG payment + (DSH payment percentage x DRG payment) + (IME payment percentage x DRG payment) + (readmission payment percentage x DRG payment) + (HVBP payment percentage x DRG payment)

IPPS Capital DRG Payment= [(capital standardized amount x DRG Weight] x wage index $^{0.69}$

Total IPPS capital payment= Capital DRG payment x (DSH payment percentage x Capital DRG payment) + (IME payment percentage x Capital DRG payment)

If applicable:

Final Total IPPS operating payment= (low volume percentage x total IPPS operating payment) + (1 percent HAC reduction x total IPPS operating payment)

Total IPPS Payment= Final total IPPS operating payment+ Total IPPS capital payment

Nearly all of the inputs in the formula to calculate the hospital payment are hospital-specific and as a result, it contributes to variation in Medicare prices across the country for the same services.

Example of Variation in Price for MS-DRG 470 Major Hip/Knee Replacement without Complications in 2015

Percentile Payment	**Medicare Reimbursement**
90th Percentile	$17,763.21
75th Percentile	$13,145.50
50th Percentile	$11,726.20
25th Percentile	$10,657.02
10th Percentile	$9,900.55
Base DRG payment without add-on factors	$11,493.98

This chart above shows that depending on the hospital's location, relative wages, performance on quality indicators, teaching hospital status and level of indigent care provided, Medicare reimbursement can vary from approximately $9900 to $17700 for the same procedure. Without these adjustments, the Medicare hospital reimbursement would have been $11,493.98.

Overview of Geographic Variation Provisions in the Affordable Care Act

The rapid increase in health care spending has long been an issue in the U.S health care system with concerns that health care spending is growing at a faster rate than the economy. Balancing the costs of a health insurance mandate was a major focus of the Affordable Care Act. However, it has been unclear what the most effective approach is to curb health care spending without impacting health outcomes and diminishing quality of care. Furthermore, it has been unclear whether additional spending improves health outcomes or quality of care. During the drafting of the Affordable Care Act, there was attention focused on Medicare payment reform and how different parts of the country had different levels of Medicare spending, Medicare utilization and health outcomes.

The Affordable Care Act had a number of provisions to address geographic variation at the national level and within the Medicare approach to payment, which demonstrates the concern for variation in Medicare spending across the country. In addition, during the drafting of the Affordable Care Act, the Secretary of Health and Human Services promised to have the Institute of Medicine submit a report on issues of geographic variation in Medicare spending.

Section 399HH established national healthcare priorities to be implemented by the Secretary. One of the priorities was to "reduce health disparities across 9 health disparity populations…and geographic areas of care." Section 931 required quality measure development by the Centers for Medicare and Medicaid Services and the Agency for Healthcare Research and Quality and required measure development for "the equity of health services and health disparities across health disparity populations… and geographic areas."

There were several provisions to examine geographic variation in spending for physicians. Section 3102 of the Affordable Care Act required an analysis of "the current methods of establishing practice expense geographic adjustments". Section 3137 of the Affordable Care Act required an examination of geographic variation in Medicare spending for hospital inpatient payments. The Act required the report to include an examination of the wage index, the geographic adjustment to Medicare inpatient payments, as well as an examination of other potential data sources to measure wage levels that better account for staffing differences and take into consideration within state and across state variation. Section 3001 of the Affordable Care Act, which established the hospital value based purchasing payment program, modifies hospitals' inpatient payments (either bonus payments or penalties) based on their performance on specified measures. This section also created the Medicare spending per beneficiary indicator which measures a hospital's Medicare spending per beneficiary as an indicator of a hospital's efficiency. The spending per beneficiary measure can be adjusted for factors such as age, sex, and severity of illness.

Section 1109 of the Affordable Care Act

Section 1109 of the Affordable Care Act was a brief provision that directed CMS to distribute $400 million during FY 2011 and FY 2012 to hospitals located in the quartile of counties with the lowest Medicare Part A and Part B spending per beneficiary. The provision required that the Part A and Part B spending per beneficiary by county be adjusted for age, sex and race. The acute care hospitals located in those counties with the lowest Medicare Part A and

Part B spending per beneficiary qualified to receive the funding. The law required that the money be distributed based on a factor of the qualifying hospital's Medicare IPPS payments relative to the total IPPS payments of all the qualifying hospitals. The intent of the provision was a short-term benefit to hospitals that received less Medicare reimbursement. In addition, the provision was a short-term adjustment to alleviate perceived inequities in spending across the country.

In the August 16, 2010 Federal Register, CMS established its methodology for calculating the Medicare Part A and Part B spending per beneficiary at the county level ~~measure~~. In addition, it identified the hospitals located in the counties with the lowest spending per beneficiary and it determined the distribution of the spending to the qualifying hospitals. First, CMS established its methodology for calculating the Medicare Part A and Part B spending per beneficiary measure in the same manner that it calculates the Medicare Advantage (the Medicare managed care insurance option for Medicare beneficiaries) capitation rates, which are also at the county level. CMS used historical claims data to determine Medicare Part A and Part B spending at the county level. In addition, CMS established an adjustment methodology that accounts for differentials in spending by age, sex and race. This was the first time CMS had calculated a spending adjustment for race, which was only done because it was required by law. Similar to the method for calculating Medicare Advantage capitation rates, the adjustments were determined using a linear regression model with age-sex regression categories. A linear regression model was also used to determine how to adjust Medicare Part A and Part B spending by race. CMS chose to categorize race into four categories, and beneficiaries were categorized based on self-identification. The four categories were White, Black, Hispanic and Other. The "Other" category primarily contained beneficiaries who identified themselves as Asian, Pacific Islander or Native American.

CMS determined the county spending adjusted for age, sex and race and ranked the counties in order of spending. There were a total of 3142 counties in the country and 786 counties in the lowest quartile of spending. CMS identified 400 acute care hospitals located in those counties as qualified to receive the bonus payments. CMS determined how to distribute the money to the qualifying hospitals by establishing weighting factors for each qualifying hospital based on the hospital's Medicare IPPS payments in FY 2009 relative to the total Medicare IPPS payments for all qualifying hospitals in FY 2009, using FY 2009 Medicare claims data, so hospitals located in areas with the lowest Medicare spending per beneficiary that received more Medicare payments received a higher share of the $400 million. The states that received the most money were New York, Virginia and Wisconsin. There were two lump sum payments to the qualifying hospitals, the first in July 2011 and the second in April 2012 to distribute the $400 million. The first payment distributed $250 million and the second payment distributed $150 million. Table 1 shows the distribution of payments by State.

Table 1: Distribution of Section 1109 payments by State

State	Number of Eligible Hospitals	Payment (in millions)	Percentage of Total Funding
Alabama	4	2.64	0.66%
Arizona	5	4.39	1.10%
Arkansas	6	8.07	2.02%
California	6	5.80	1.45%
Colorado	3	0.77	0.19%
Georgia	11	17.81	4.45%
Hawaii	14	15.11	3.78%
Idaho	11	10.45	2.61%
Illinois	6	4.63	1.16%
Indiana	12	7.99	2.00%
Iowa	20	33.33	8.33%
Kansas	4	1.81	0.45%
Kentucky	2	0.49	0.12%
Maine	4	3.44	0.86%
Michigan	8	4.52	1.13%
Minnesota	13	10.66	2.67%
Mississippi	4	3.39	0.85%
Missouri	11	19.41	4.85%
Montana	9	10.08	2.52%
Nebraska	4	4.07	1.02%
New Mexico	20	15.93	3.98%
New York	50	46.24	11.56%
North Carolina	7	2.89	0.72%
North Dakota	5	9.41	2.35%
Ohio	2	0.55	0.14%
Oklahoma	1	1.06	0.27%
Oregon	21	23.85	5.96%
Pennsylvania	13	16.61	4.15%
South Carolina	1	2.43	0.61%
South Dakota	19	15.18	3.80%
Texas	3	1.27	0.32%
Utah	11	1.96	0.49%
Vermont	2	0.96	0.24%
Virginia	31	41.51	10.38%
Washington	12	15.07	3.77%
West Virginia	2	0.22	0.05%
Wisconsin	40	33.35	8.34%
Wyoming	3	2.64	0.66%
Total	**400**	**400.00**	**100.00%**

When CMS announced the implementation of Section 1109 and the distribution of payments, the New York Times reported that "the result was not exactly what Congress or hospital lobbyists had expected." According to the New York Times, "Members of Congress from Iowa, Minnesota, Washington and Wisconsin secured extra money in the new health care law to reward low-cost hospitals in their states, which they said had long been underpaid by Medicare. But it now turns out that New York will get more of the money than any other state, and some of the chief proponents of the bonus payments will not receive any." The article noted that geographic disparities in Medicare spending were a critical component of the healthcare reform debate during which members of Congress particularly in the Midwest and Northwest complained that their hospitals were underpaid for their services. Additionally, the article pointed out that the hospitals that received the bonus money were largely in rural areas, small towns and medium-size cities and that New York had the most hospitals, receiving the largest share of the $400 million (Pear, 2010).

It is also worth noting that since the implementation of Section 1109, the Medicare program has sought to move towards payment for value of healthcare as opposed to paying for volume of services. On April 2015, the Medicare Access & CHIP Reauthorization Act of 2015 (MACRA) was enacted, that repealed the Sustainable Growth Rate (SGR) formula for determining Medicare payments for clinicians' services, and established a new framework for rewarding clinicians for value over volume, and streamlined other existing Medicare quality reporting programs for providers by combining the existing CMS quality reporting programs into one new system. After repealing the SGR formula, MACRA creates the Merit-Based Incentive Payment System (MIPS) which combines various quality reporting programs for physicians into a single consolidated program with four weighted performance categories upon which eligible professionals (EPs) will be assessed: Quality; Resource Use; Clinical Practice Improvement Activities; and Meaningful Use of Certified EHR Technology. MACRA requires that CMS develop and provide clinicians with a Composite Performance Score that incorporates MIPS performance on each of these categories and based on this Composite Performance Score, physicians may receive additional reimbursement or penalties on their Medicare payments. MACRA also provides incentives for participation in certain Alternative Payment Models in which physician participants are not subject to MIPS adjustments, but instead receive a lump sum incentive payment. As a result, MACRA encourages expansion of these alternative payment models available to physicians. These new policies that are seeking to revise Medicare physician payment reimbursement demonstrate that Medicare is moving away from paying for volume to paying for better quality of care. This study could help to inform policy makers and other stakeholders if providing more funding could improve quality of care to Medicare beneficiaries.

Study Goals and Objectives

The purpose of this study is the following:

- To evaluate whether these Section 1109 hospitals, located in areas with low Medicare spending per beneficiary, provide equivalent quality of care in terms of Medicare readmission rates and Medicare mortality rates as compared to the hospitals that are not located in counties with the lowest Medicare spending per beneficiary.
- To examine whether the quality of care provided by Section 1109 hospitals improved more after receiving the additional funding, as compared to non-Section 1109 hospitals and;.
- To evaluate whether the amount of the additional funding that Section 1109 hospital received impacts the extent to which quality of care improved.

Ultimately, this study seeks to assess if Medicare gives hospitals more money, do patients receive better quality care.

These findings are relevant to policymakers given the scrutiny of variation in Medicare spending across the country and the various pieces of legislation enacted to examine this issue of geographic variation in Medicare spending. Furthermore, these findings can inform Medicare as it moves towards paying for value over volume as indicated by the intent of the MACRA legislation.

The second chapter of this study provides a literature review on sources of geographic variation in healthcare spending, how to measure quality of care and how healthcare spending impacts quality of care. The literature review will demonstrate that there is no clear pattern on how healthcare spending impacts quality of care or what contributes to geographic variation in healthcare spending. The third chapter describes the methodological approach of this study, including the research questions, hypotheses tested, data sources and statistical methods. The fourth chapter presents the findings of the study and the last chapter will present the policy implications of the results.

Chapter 2: Literature Review

A literature review was conducted to find existing research on several aspects of this study: 1) determinants of geographic variation on Medicare reimbursement, 2) studies that assess the relationship of quality of care and Medicare reimbursement, 3) studies that utilize CMS mortality rates and readmission rates as indicators of hospital quality of care, 4) studies that examine health policies using the difference-in-difference method and 5) studies that examine health policies using a propensity score matching method. Several PubMed searches were conducted to inform this literature review. A search on PubMed was conducted using search terms “geographic variation” and “Medicare spending” and yielded 42 results on January 11, 2016. A search on PubMed on ‘“Medicare spending” and “quality of care”’ produced 239 results. A search on PubMed was also conducted on the use of mortality rates and readmissions rates as indicators of quality of care. A literature review search was conducted on the methods for this study to identify if they are appropriate to use in health policy studies pertaining to Medicare. A literature search was conducted on studies including “difference in difference” and “Medicare” and “propensity score” and “Medicare”. Lastly, a literature review search was conducted on Section 1109 of the Affordable Care Act which yielded no results. The subsequent sections summarize the research by search topic with a discussion of the relevance of each section to the study aims.

Literature Review of Determinants of Geographic Variation on Medicare Reimbursement

There are several studies on the determinants of geographic variation in Medicare spending and the relationship of geographic variation in spending with outcomes and utilization. The research on the determinants of geographic variation in Medicare spending can be categorized into the following groups: 1) regional differences in costs of physician practice, (Mitchell & Davidson, 1989; Pope, Welch, Zuckerman, & Henderson, 1989), 2) payment variations due to policy decisions and market forces (MedPAC, 2009; Centers for Medicare & Medicaid Services, 2009), 3) provider training and supply as well as supply of other health care resources (Baicker & Chandra, 2004; Cooper, Cooper, McGinley, Fan, & Rosenthal, 2012; Ricketts & Belsky, 2012; Welch, Miller, Welch, Fisher, & Wennberg, 1993; Wennberg & Cooper 1999; Zuckerman, Waidmann, Berenson, & Hadley, 2010), 4) population demographics and socioeconomic status (Cooper et al., 2012; Ricketts & Belsky, 2012; Rosenthal, 2012; Zhang Steinman, & Kaplan, 2012; Zuckerman et al., 2010), 5) health status and prevalence of particular diseases (Reschovsky, Hadley, Saiontz-Martinez, & Boukus, 2011; Rosenthal, 2012; Sargen, Hoffstad, & Margolis, 2012; Zuckerman et al., 2010), and 5) service use arising from patient preferences (Rosenthal 2012; Wennberg & Cooper, 1999; Zhang et al.,2012), and 7) discretionary decisions by health care providers (Cooper et al., 2012).

Geographic variation research began in the 1970s where initial studies showed regional differences in utilization when adjusted by various population demographics. The first studies by Wennberg and Gittlesohn, examined variation in rates of surgical procedures in Maine and Vermont (Wennberg, Gittlesohn, 1973). Studies continued in the 1980s with research showing great variation in hospital use and mortality by Medicare beneficiaries in Boston versus New Haven, when adjusted for age, sex and race (Wennberg, 1989). National studies found variation among "hospital referral regions", which were defined as regional health care markets for tertiary medical care that generally requires the services of a major referral center. These regions were found to vary with respect to Medicare spending, supply of physicians and hospitals, rates of surgical procedures and hospitalizations (Dartmouth Atlas Project, 2007). These geographic variation studies spurred a debate during health care reform, as studies found that overutilization reduced quality of care, harmed patients and increased Medicare spending (Wennberg, Fisher, 2008). In the media, Atul Gawande's New Yorker article raised awareness that variation in physicians' chosen practice patterns drives variation in Medicare costs observed, even in cities geographically nearby one another (Gawande 2009).

This literature review is focused on spending for Medicare beneficiaries and impact on utilization and health outcomes and found a body of research on the factors driving geographic variation in spending and whether policy can influence this. The Dartmouth Atlas studies examine spending at the state level, hospital referral region (HRR) and hospital service area (HSA) levels. In general, the Dartmouth Atlas group focused on the Medicare Fee-for-Service beneficiaries and adjusted variation for age, sex and race. The factors that they examine at the regional levels included variation in spending, utilization and resources. Spending analyses examined Medicare per beneficiary spending; utilization analyses examined rates of procedures or events at the regional level; and resource studies examined the quantity of staff or equipment used at the regional level.

The 2013 report conducted by the Institute of Medicine (IOM), commissioned by the Secretary of Health and Human Services after the enactment of the Affordable Care Act, examined the degree of geographic variation. In the IOM study, researchers were tasked with evaluating geographic variation in health care spending levels and growth among Medicare, Medicaid and other insured and uninsured populations, and making recommendations for changes to Medicare payments based on this evaluation. Researchers observed that age, sex and health status accounted for some geographic variation. Other demographic factors such as race, income, insurance, employer characteristics and market characteristics had trivial effects in reducing geographic variation, once health status was accounted for in the model. The study found that even when accounting for age, sex and health status, a substantial amount of geographic variation, ranging from 40 percent to 70 percent, remained unexplained. Furthermore, the study found that geographic variation in both Medicare and private spending was a real phenomenon and that high-cost areas in 1 year had consistently high costs in other years. Other observations included that areas with high costs in the treatment of 1 condition were somewhat more likely to have high costs in treating other conditions, but higher spending was not associated with better outcomes or higher quality care, either overall or when viewed from the perspectives of individual health conditions. Lastly, the study found that much of the variation in Medicare spending per beneficiary was in post–acute care (such as care provided by home health agencies, skilled nursing facilities, rehabilitation facilities, long-term care hospitals, and hospices). Variation due to post–acute care services contributed to 73% of the geographic variation in Medicare spending, even though these services only accounted for 13% of Medicare spending. After post-acute care services, the largest remaining overall expenditure variation, an estimated 27%, was due to variation in inpatient services. The study found that variation in outpatient procedures, visits, and diagnostic testing accounted for little of the overall geographic variation. (IOM, 2013)

As described earlier, studies on factors that influence geographic variation in Medicare spending can be categorized by different factors such as utilization, access, patient characteristics and preferences. A general observation from the literature review is that there are no consistent results regarding what factors explain geographic variation in Medicare spending. Furthermore, the literature review shows that there are many factors that contribute to geographic variation in Medicare spending, many ways to measure those factors, various units of geography and many ways to measure Medicare spending. Despite the large amount of literature on determinants that can explain geographic variation in Medicare spending, much of the geographic variation in Medicare spending remains unexplained.

Several studies have examined how provider training and supply, as well as supply of other health care resources, influence Medicare spending. The literature review found that there were no consistent results on how provider supply affects the geographic variation of Medicare spending. Furthermore, the literature review found that there are a variety of ways to measure physician supply, the geographic unit and Medicare spending. One study found that states where more physicians are general practitioners showed lower cost per beneficiary. Furthermore, increasing the number of general practitioners in a state by 1 per 10,000 population (while decreasing the number of specialists to hold constant the total number of physicians) was found to be associated with a reduction in overall annual spending of $684 per beneficiary. Conversely, the study found that States where more physicians are specialists have higher cost per Medicare beneficiary. The estimated effect of increasing the fraction of specialists by 1 per 10,000 resulted in an increase in annual spending of $526 per beneficiary. Lastly, the study found that the supply of nurses does not seem to affect either the use of high-quality care or total spending (Baicker & Chandra, 2004). Similarly, another study examined variations in Medicare per beneficiary costs at the hospital service area level and determined whether physician supply and the specialty of physicians have significant relationships with cost variation. Using correlational analysis as well as bivariate plots and fixed effects linear regression models, the study examined relationships between the physician supply per 1,000 beneficiaries categorized by specialty with covariates of poverty rate, per capita income and college education and per capita Medicare spending. The study found that the relative numbers of specialists or primary care physicians in a hospital service area were likely not the major correlate of Medicare costs. However, costs were strongly related to the sociodemographic characteristics of the hospital service areas and the overall supply of physicians. There were mixed correlations with the specialist supply depending on the interaction of the proportion of the physician supply who were international medical graduates (Ricketts & Belsky, 2012). On the other hand, a different study found that access to primary care services reduces Medicare spending. Specifically, the study found that hospital referral regions with high primary health center penetration had 10% lower Medicare spending by fee-for-service elderly beneficiaries (Sharma, 2014). Even early studies of geographic variation found that physician supply and utilization greatly influenced Medicare spending. A study by Welch, Miller, Welch, Fisher and Wennberg in 1993 examined spending at the metropolitan statistical area (MSA) level and found that spending for physicians' services varied greatly among MSAs, with those for the areas with the lowest and the highest rates differing at least twofold on each measure of physician spending. The study found that areas with high rates of admission tended to have high levels of payment to physicians for inpatient care per admission, and areas with high payments for inpatient services tended to have high payments for outpatient services. Spending was not related to the number of physicians per capita but was lower in MSAs with a high proportion of primary care practitioners (Welch, Miller, Welch, Fisher and Wennberg, 1993). Lastly, another study found that physician supply did not influence Medicare spending and this study used linear multivariate-regression models that had as the dependent variable price-adjusted Medicare spending per beneficiary. The independent variables included area-level measures of the supply of health care resources (numbers of hospital beds and physicians per 1000 elderly population, percentage of physicians in primary care, number of resident physicians per bed, and whether or not the nearest hospital with ≥100 beds was a teaching hospital). The study found that differences in the supply of medical resources were neither significant nor quantitatively important for understanding Medicare spending (Zuckerman, Waidmann, Berenson, & Hadley, 2010).

The literature review included several studies that examined how population demographics and socioeconomic status impact geographic variation in Medicare spending. One study examined spending at the zip code level and found that understanding geographic variation among large regions, such as counties and HRRs, requires disaggregation into their constituent ZIP codes and census tracts. Second, residents of low-income ZIP codes have greatly increased rates of disability and hospital utilization and that poverty varies geographically and its variation explains a great deal about geographic variation in health care utilization and spending (Cooper, McGinley, Fan, & Rosenthal, 2012). As described earlier, one study found that costs were strongly related to the sociodemographic characteristics of the hospital service areas. This study measured sociodemographic characteristics with respect to the proportion of families in poverty, per capita income, the proportion of the population with a college degree, and the proportion of the population that was African American and found that at the HSA level, these characteristics were strongly related to Medicare Part A and Part B spending per beneficiary (Ricketts & Belsky, 2012). Other factors found to contribute to variation in spending include racial or ethnic differences, socioeconomic status, insurance status and education. Some studies have found that non-whites have higher spending and more utilization than whites (Cooper, 2010). However, another study concluded that health status and supply of medical resources do not fully account for variation in Medicare spending and that more data are needed to identify the other causes of the variation. Specifically, the study found that health status accounted for 29 percent of geographic differences in per beneficiary spending; adjustment for differences in supply of medical resources did not further reduce the differences in per beneficiary spending between the top and bottom spending quintiles of HRRs (Zuckerman, 2010). Another study found that State-specific factors, such as income, health care capacity, and the share of elderly residents, are important factors in explaining the level of per capita Medicare spending variation among states (Cuckler, 2013).

There have been several studies that examined health status and prevalence of specific diseases and their relationships to geographic variation in Medicare spending. These studies have found that for specific conditions, certain factors can contribute to geographic variation in Medicare spending. One study examined Medicare beneficiaries with diabetic complications and geographic variation in spending. The study used linear regression analysis to determine the effect that diabetic disease severity (rates of macrovascular and microvascular complications) and the utilization of inpatient and outpatient services (hospital admission rates and outpatient visits) have on per capita expenditures and mortality rates within a geographic region. The study found that increased Medicare spending was not associated with improved one-year survival for patients with foot ulcers or lower extremity amputations. However, hospital admissions, macrovascular complications and microvascular complications occurred more often in patients with foot ulcers living in higher spending regions. The study found that per capita Medicare spending varied considerably among hospital referral regions. Moreover, there was no statistically significant reduction in all-cause mortality associated with higher Medicare spending (Sargen, Hoffstad, & Margolis, 2012). Finally, one study examined patterns of prevalence, utilization, and expenditure for Medicare beneficiaries with multiple (6 or more) chronic conditions at the State level and found there is variation by State in the prevalence of beneficiaries with 6 or more chronic conditions. They also found that beneficiaries with 6 or more chronic conditions had higher readmission rates, Medicare spending and ED visits than average, although there was much variation in these outcome variables by State when looking at only Medicare beneficiaries with 6 or more chronic conditions (Lochner et al, 2013). Another study examined the extent to which the ESRD population contributes to geographic variation in Medicare spending. Using an ordinary least squares regression model with average annual Medicare payments per patient with ESRD as the dependent variable, the study found that the predictor variables of demographic descriptors (average age, race, and sex distributions by region) and one case-mix indicator (percentage of diabetic versus non-diabetic cases of ESRD) explained 80 percent of variance in spending. Overall, three factors accounted for most of the explained variation: type of renal replacement therapy, standardized hospitalization ratio (SHR) for dialysis patients, and Medicare area wage index explained approximately 70 percent of the geographic variation in spending. Spending varied little with the racial, age and gender distribution of the ESRD population. Area socioeconomic characteristics, like level of education and income, had stronger relationships to spending (Hirth, 2011). Another study examined variation in utilization among different categories of services and its effect on geographic variation in spending. The study found that high-use geographic areas were not necessarily high-use sites across all service categories and similarly, low-use sites were not necessarily low-use sites across all service categories. Notably, the study found that durable medical equipment, such as wheelchairs and diabetic supplies, and Part B drugs showed the greatest variation. Overall, the study found that inpatient care, home health, and durable medical equipment contributed the most to geographic variations, followed by skilled nursing facility, hospital outpatient, and other physician visit services (Reschovsky et al, 2012).

Another study examined if there are trends in geographic variation over time and whether regions with high Medicare expenditures in a given setting remain high cost over time. The study found that drivers of Medicare spending have changed over time such that high inpatient hospital and home health spending have always been associated with high total Medicare spending, but high spending on hospice care and skilled nursing facility care has become increasingly associated with high total Medicare spending from 1992 to 2010. The study also found that relative spending levels are persistent over time where an HRR deemed high cost in 1992 is likely to be high cost in 2010. This finding is true both for total Medicare spending as well as for certain categories of spending in home health, inpatient hospital, and outpatient hospital spending. Lastly, the study found that there is some evidence of regression to the mean for total

Medicare spending, particularly for spending on certain types of post-acute care (hospice and skilled nursing facility) (Chiklis, 2010).

Patient preference and its relationship to utilization also influences geographic variation in Medicare spending. One study assessed the extent to which differences in patients' preferences across geographic areas explained differences in traditional fee-for-service Medicare spending across Dartmouth Atlas of Health Care Hospital Referral Regions. Using ordinary least squares models in which the dependent variables were Medicare spending per beneficiary and the independent variables included the share of respondents answering the preference questions affirmatively, the study found that the patient preference measures had a modest but statistically significant association with area average total Medicare spending per beneficiary. The study also found that the number of physicians per 100,000 population was significantly negatively related to the spending. The number of hospital beds per 1,000 people was significantly positively related to the spending and the mortality rate of Medicare beneficiaries, adjusted for age, sex, and race, was positively related to spending variation (Baker, 2014). Another study found significant variation in prescription drug use at the HRR, State and regional level after adjusting for population characteristics such as age, gender, race and insurance status. The study found that prevalence of underlying disease alone did not explain the geographic variation in prescription drug use. The authors theorized whether disease severity and other discrete health status measures, or a patient's preferences and explicit requests and expectations for antibiotic treatment influenced variation in prescription drug use and in turn geographic variation in spending for drugs by the Medicare population (Zhang, 2012).

Overall, this literature review has demonstrated that there are several ways to measure spending at the regional level, be it at the county level, State level, hospital spending area or hospital referral region. The level at which spending is measured can influence the results. Furthermore, the literature review has demonstrated that there are multiple factors that can contribute to geographic variation in spending including market characteristics, patient preferences, the supply of resources, and characteristics of the patient populations. However, the literature review has shown that there are conflicting results on how and the extent to which these factors influence geographic variation in Medicare spending and that there is no clear consistent cause of geographic variation in Medicare spending. Due to the complexity of this issue, policymakers are aware that geographic variation in spending is a concern, but have yet to identify ways in which Medicare payment policy can alleviate geographic variation in spending.

Literature Review of the Relationship of Medicare Spending and Quality of Care

One of the aims of this dissertation is to examine whether changes in Medicare spending result in changes in quality of care. Studies have shown mixed results in whether or not the level of Medicare spending improves or diminishes quality of care. Some studies have found that higher spending does not result in better patient care, better outcomes or better patient satisfaction while other studies have shown the opposite results. This literature review divides studies based on these two opposite sets of results, into the following categories: 1) Studies on higher healthcare spending and worse quality outcomes and 2) Studies on higher healthcare spending and better quality outcomes. Before describing those studies, it is worth noting that the major research on geographic variation in spending and quality of care are the studies from the Dartmouth Atlas Project. These studies found that regional variations in Medicare per capita spending by HRR did not result in higher-quality care, in terms of specific evidence-based health services or in terms of greater access to basic health care.

Specifically, one of these studies found that higher levels of spending at the HRR level did not improve certain process of care measures: AMI patients in the highest quintile of Medicare spending HRR were no more likely to receive acute reperfusion, were less likely to receive aspirin at admission or discharge and angiotensin-converting enzyme inhibitors in the setting of a low ejection fraction, and were more likely to receive beta-blockers, compared to the lowest quintile. The variation in spending in HRRs was attributed to more frequent hospital visits, more frequent physician visits, greater use of physician specialists, and more frequent diagnostic tests and minor procedures, and the quality of care was no better in higher-spending regions in terms of process of care measures (Fisher, 2009).

The second analysis based on the Dartmouth Atlas research regarding regional variations in Medicare per capita spending found that the higher spending attributed to more hospital visits, physician visits and more procedures did not improve certain health outcomes. The study found that the pattern of practice observed in higher-spending regions did not lead to improved mortality rates, slower decline in functional status, or improved satisfaction with care (Fisher, 2003). Another Dartmouth Atlas study found that a large proportion of Medicare spending,--nearly 20 percent--appears to provide no benefit in terms of survival or improvement in quality of life (Skinner et al, 2005). Finally, a study by Landrum examined whether greater service use among colorectal cancer patients in high-spending areas improves health outcomes and found mixed associations with end of life inpatient Medicare spending at the HRR level and recommended care for each of the 6 quality of care indicators for colorectal cancer, but higher spending was associated with higher use of costly chemotherapy treatment. In addition, the study found that increasing end of life inpatient spending at the HRR level was associated with increased non-cancer mortality, but no association was found with end of life spending and all-cause or cancer mortality (Landrum, 2008).

Studies on Higher Healthcare Spending and Worse Quality Outcomes

Another set of studies examined the relationship of spending and impact on outcomes and generally found that outcomes were worse with higher spending. This next section reviews those studies that found that relationship. One study by Baicker looked at the relationship of quality of care measured as a composite of twenty-four quality measures developed by the Medicare Quality Improvement Organizations with Medicare spending per beneficiary at the state level. Efficiency was measured in terms of Medicare spending per beneficiary at the State level, based on Medicare fee-for-service claims data, adjusted for age, sex and race. The study found an inverse correlation: States with lower spending per beneficiary had higher quality of care and conversely, States with higher spending per beneficiary had lower quality of care. The study suggested that the mix of the physician workforce plays a critical role in the use of highly effective care wherein states with more general practitioners had lower spending per beneficiary and better quality of care. Specifically, the study examined the sources of higher Medicare spending for States and found that States with hospitals with higher percentages of ICU patient days for the beneficiaries' last 6 months of life had higher Medicare spending. Furthermore, States where more physicians are general practitioners showed greater use of high-quality care and lower cost per beneficiary (Baicker, 2004).

Another study looked at the relationship of quality of care measured in terms of amputation rates and Medicare spending on vascular care. The study found that there is geographic variation in spending on vascular care, with vascular costs varying more than two-fold across hospital referral regions in the United States. The study found that some regions spent less than $13 000, on average, in the year prior to amputation, whereas other regions spent $30 000 or more in the year prior to amputation The variation was due to differences in the use of revascularization treatments, rather than differences in patient characteristics or costs related to the amputation itself. Overall, the study found there is little evidence to suggest that higher spending on invasive vascular care, especially endovascular care, in the year prior to amputation is associated with lower regional rates of amputation (Goodney, 2014).

Studies on Higher Healthcare Spending and Better Quality Outcomes

In contrast, some studies have found specific instances in which more spending resulted in improved health outcomes or lower spending resulted in lower quality of care. One study by Jha found that hospitals with lower costs had marginally lower quality of care. In this study, costs were measured as a ratio of a hospital's average cost per case for Medicare patients, based on Medicare hospital cost report data, to the predicted average cost per case for Medicare patients. The outcome variable of the study, quality of care, was measured based on a summary performance score on performance related to treatment of AMI, heart failure and pneumonia. In addition, the study examined costs and the 30-day mortality rates for AMI. The study measured costs as a ratio of observed costs versus predicted costs. The study found that hospitals with lower costs had slightly lower quality of care in terms of these performance measures (Jha, 2009).

Another study by Romley found that increased hospital spending was associated with lower risk-adjusted inpatient mortality among Medicare beneficiaries. Specifically, the study found that patients admitted into hospitals in the highest spending quintile had lower risk-adjusted inpatient mortality for certain conditions compared with those admitted to hospitals in the lowest spending quintile. (Romley, 2013). This author did another study on the association between hospital spending—the sum of spending on inpatient physician visits, hospital room charges, laboratory testing, diagnostic imaging, medication administration, and procedures—and inpatient mortality for the periods 1999 to 2003 and 2004 to 2008 for six major medical conditions treated in 208 California hospitals. Controlling for hospital size, volume, teaching status and managed care penetration, the study found that greater hospital spending was associated with lower inpatient mortality for all six diagnoses (Romley, 2011). Similarly, another study, which had results contrary to the Dartmouth Health Atlas study, found that increased medical care and increased spending is associated with a statistically significant reduction in mortality rates and avoidable hospitalization for Medicare beneficiaries that received hospital care between 2004 and 2006 (Hadley et al, 2012). An investigation building on the Baicker study found a correlation between higher Medicare per enrollee spending by State and worse quality of care based on a composite measure. These findings were similar to the results of the Baicker study. However, the study found a strong correlation between higher total per capita unadjusted spending and better quality under the composite quality score and a strong correlation with increasing non-Medicare spending per capita and better quality under the quality composite measure (Cooper, 2008).

A meta-analysis was conducted in 2013 that reviewed studies on the association between health care quality and cost published between 1990 and 2012 (Hussey, 2013). Sixty-one studies were reviewed and categorized based on the level of analysis (at the provider level or area level), type of quality measure, type of cost measure, and method of addressing confounders including health status. Of the 61 studies, the findings of the association between health care cost and quality were inconsistent, such that 34 percent reported a positive or mixed-positive association (meaning higher cost associated with higher quality); 30 percent reported a negative or mixed-negative association; and 36 percent reported no difference, an imprecise association, or a mixed association. The study findings on the association between cost and quality were also inconsistent at the various levels of analysis studied, where hospital-level analyses were slightly more likely to report a positive association (45 percent of studies had a positive association and 34 percent had a negative association), whereas area-level studies were more likely to report a negative association (17 percent of studies had positive associations and 42 percent had negative associations). All of the studies evaluated were observation studies, not experimental design studies. These observational studies used three approaches for accounting for health status as a confounding variable: 1) natural randomization, which involved assignment of patients to treatment groups using a natural feature (such as co-morbidities or smoking status, as opposed to the controlled assignment used in randomized, controlled trials; or 2) instrumental variables analysis, which uses instrumental variables (observable factors that influence treatment but do not directly affect the outcome measure) to mimic randomization; or 3) multivariable regression analysis, which adjusts for the effects of observable health status using statistical methods but does not account for unmeasured health status. Most of the studies, 77 percent, used multivariable regression analysis (Hussey, 2013).

While studies described so far have shown mixed results in the relationship between spending and health outcomes, survival or quality of life, another study looked at the relationship between the regional variation in Medicare spending and Medicare patients' perceptions of the quality of care they receive. The study found that survey respondents in HRR areas with low per capita Medicare Part A and B spending did not have more perceived unmet needs for cardiac tests or treatments compared to survey respondents in high per capita Medicare Part A and B spending HRRs. In addition, survey respondents with higher health care utilization (in terms of more doctors' visits, more types of doctors visited, more cardiac tests) were in HRRs with higher Medicare per capita spending, and they had a greater perceived unmet need for seeing specialists, despite the greater likelihood of seeing specialists in those HRRs. (Fowler et al, 2008).

In summary, the studies presented in this literature review demonstrate a variety of findings on how spending for healthcare services impacts health outcomes where in some cases greater spending is associated with better quality of care or outcomes and in other cases, lower spending is associated with better quality of care or outcomes . The literature review also presents a variety of ways to measure healthcare spending and quality of care.

CMS Alternative Payment Models and Quality of Care

More recent literature has shown how changes in Medicare reimbursement under the Affordable Care Act, like movement towards alternative payment models, influence quality of care. This is relevant to this dissertation because it shows how hospitals' incentives change with changes in Medicare reimbursement and how that also influences quality of care. Accountable Care Organizations (ACOs) were developed under the Affordable Care Act as a tool to control Medicare spending and improve quality of care. Under the Medicare ACO program, participating provider groups are rewarded financially for limiting the use of health care and improving the quality of care. Specifically, ACOs that achieve spending below the targets set by Medicare are eligible to receive a share of the savings However, if spending exceeds the target, some ACOs must return a share of the excess spending to Medicare. One study examined the effect of ACOs on patient satisfaction scores, using HCAHPS patient survey data. Patient satisfaction scores were based on overall ratings of care and ratings for physicians, timely access to care, interactions with the primary physician, and care coordination and management. The covariate was an HCC risk score developed based on age, sex, race or ethnic group, whether disability was the original reason for Medicare eligibility, and whether the respondent had end-stage renal disease or any of 27 conditions. Using linear regression and a difference-in-differences approach to estimate changes in patients' experiences in the ACO group from the pre-intervention period to the post-intervention period, the study found that ACO contracts were associated with meaningful improvements in some measures of patients' experience and with unchanged performance in others (McWilliams, 2014).

Another study estimated the impact of three provider-focused policies on geographic variation in Medicare spending: 1) bundled payment, 2) pay-for-performance (P4P), and 3) ACOs. The study sought to determine whether the three programs, which can significantly change provider payments, contribute to geographic variation in payments. The study evaluated whether the three policies would decrease geographic variation in Medicare spending by comparing Medicare spending in 2008 for each health referral region under the baseline case to the scenarios in which each policy (bundled payments, P4P, ACOs) were implemented. The study found that P4P had small effects on spending and did not show a strong geographic pattern by spending quintile. The ACO scenario reduced spending in all HRRs, but with a relatively weak geographic pattern. ACOs largely reduced spending in areas with high spending. Under the bundled payment scenario, there was a clearer pattern of spending increases in the lower quintiles and spending reductions in the higher quintiles (Auerbach, 2015).

Overall, the literature review has shown that there are a variety of ways to measure Medicare spending and quality of hospital care, at the regional level and hospital level. Furthermore, the literature review has shown that there are no consistent results on the association of Medicare spending and quality of care. An aim of this study is to contribute to the existing literature to determine whether providing additional Medicare spending has any impact on quality of care provided in a hospital.

Literature Review of Readmissions and Mortality as Indicators for Quality of Care

As described earlier, the outcomes of interest in this dissertation are hospital-level, condition-specific 30-day readmission rates and 30-day mortality rates for the Medicare FFS population. These measures are used in this dissertation as a way to evaluate a hospital's quality of care. There have been many studies using these indicators as measures of quality of care for hospitals, which supports the use of these measures in this study. This next section reviews some of these studies.

Readmissions cause a high burden to healthcare systems and patients. In 2008, nearly 20% of Medicare patients were readmitted within 30 days after hospital discharge, associated with an estimated annual cost of $17 billion (Jencks, 2009). Readmissions were thought to be an indicator of quality of care, as they were seen as related to postoperative complications (Fischer, 2014). Furthermore, there was much regional variation in readmissions rates, so readmissions were also viewed as potentially avoidable. Reducing readmission rates became a high policy priority for Medicare when the program first began publicly reporting Medicare FFS readmission rates for hospitals on the CMS Hospital Compare website, which is a consumer website that shows quality of care indicators for hospitals. Subsequently, through a provision in the Affordable Care Act, beginning in October 2012, CMS was required to reduce Medicare payments to hospitals with higher-than-expected readmission rates for certain high volume, high cost conditions. Lastly, under the Affordable Care Act CMS launched the Community-based Care Transitions Program, a $500 million provision that provides funding to hospitals and community-based organizations to implement programs collaboratively to reduce readmissions.

These initiatives demonstrate that appropriately measuring readmissions and holding hospitals financially accountable for performance on these measures are a policy priority for Medicare.

In light of these initiatives, one study examined the extent to which Medicare's risk-standardized readmission rates change over a two-year period and whether those changes occur in a pattern that suggests that the changes are a reflection of quality of care or of random variation. The study also examined whether readmission rates were correlated with other common quality indicators, such as Medicare's risk- standardized mortality rates, volume, teaching status, and process of care measures. The study found that hospitals with higher readmission rates in 2009 tended to improve over time, while hospitals with lower readmission rates tended to worsen. The analysis explained that these changes were due in part to regression to the mean. In addition, the study found weak or inverse correlations between readmission rates and other hospital quality indicators, including risk-standardized thirty-day mortality rates, volume, teaching status, and performance under process measures. Potential explanations for these patterns include that mortality rates and readmission rates are inversely related in that low readmission rates may be due to the fact that the patients have higher mortality rates. The finding, however, does indicate that some element of hospital performance, as measured by the change in readmission rates, is due to statistical noise rather than true changes in quality of care (Parina, 2014).

Another meta-analysis was conducted to assess the validity and reliability of the readmission measures as a quality of care indicator. The criteria to assess validity and reliability of a readmission measure were as follows: 1) whether the measure was relevant based on the measure's impact on health, on policymaking and the measure's capacity to be changed by the health care system, 2) whether the measure was feasible such that the data needed to calculate the indicator was available and reliable, and 3) whether the measure has scientific soundness. The study found that the validity of readmission rates as a quality indicator is influenced by a number of factors including: 1) the rationale for the readmissions measure, 2) the clinical process that is assessed, 3) the indicator definition and the extent of case-mix adjustments, 4) the effect of competing outcomes such as mortality rates, and 5) data reliability. The study found that the definition of readmission is important to the validity and reliability of the measure, including whether a readmission is defined to be disease specific and defined to account for planned readmissions. The study found that there is high variation in overall readmission rates, but that is not the case for the rate of preventable readmissions. The study found that the time window after the index admission in which admissions are regarded as readmissions has not been consistently defined in the literature and the time window can affect the validity of the measure. Furthermore, readmission rates are influenced also by other factors beyond quality of hospital care, including length of stay, in-hospital death and patient characteristics. The meta-analysis found conflicting results on the relationship with length of stay and risk of readmissions where some studies found that there is an inverse relationship with length of stay and risk of readmission and other studies could not find any relationship. Furthermore, there have been several studies conducted on the relationship between high readmission rates and mortality rates. The review described that studies found a "modest" inverse relationship between readmission rates and mortality rates for heart failure patients, and no relationship could be observed between readmission rates and mortality rates for pneumonia and AMI, suggesting that the readmission rates and mortality rates measure different aspects of quality of care, and may not be strongly related (Krumholz, 2013). The review found several studies that measured patient characteristics and its influence on risk of readmission. There have been a number of studies that examined socioeconomic status and increased risk of readmission, although the meta-analysis noted that these characteristics have not been incorporated in readmission measures due to data limitations. The meta-analysis found that poorly accounting for these factors can severely bias the readmission rate results and comparisons among hospitals. The meta-analysis concluded that using readmission rates as a quality measure requires a clear definition of the context, including the rationale of measuring readmissions, the related care processes and the patient groups. (Fischer, 2014).

Another meta-analysis reviewed studies that examined avoidable readmissions, under the premise that readmissions are only an indicator of quality of care if it can be assumed that readmissions are avoidable. This meta-analysis reviewed studies between 1966 to July 2010 and found that the proportion of avoidable readmissions varied greatly. The study concluded that the variability makes it difficult to ascertain how many readmissions are preventable. The study found that the variation seen in these studies could reflect actual differences in quality of care, but it could also reflect the subjectivity of the outcome itself as well as differences in study characteristics, including patient and hospital types included or factors in determining avoiding readmissions (Joynt, 2014).

Another study examined whether public reporting of readmission rates affects patient outcomes. The study specifically assessed the impact of the 2009 CMS policy change on public reporting of readmissions and evaluated public reporting as a quality improvement tool. The study concluded that reporting hospital readmission rates publicly on the Hospital Compare website was not associated with improvements in outcomes (Devore, 2016).

Another study examined if hospital performance on well-established measures of surgical quality, such as adherence to surgical process measures, procedure volume, and mortality, was correlated with its surgical-readmission rates. The study found that the overall relationships with hospital quality were consistent with those observed for the composite readmission rates. All three quality measures — HQA surgical score, procedure volume, and surgical mortality — were generally associated with the procedure-specific readmission rates, although the differences were not always significant. The study found that adherence to best-practice guidelines, as reflected by the HQA surgical score, was weakly associated with marginally lower readmission rates. The absence of an independent relationship between the HQA surgical score and readmission rates may be a result of the low variation in performance on this measure (Tsai, 2013).

Overall, a review of the literature has found that there are many ways to measure readmissions, and readmission rates vary widely depending on how readmissions are defined. Other key factors that influence readmission rates are the inverse relationship of readmission rates to mortality rates and the exclusion of planned readmissions in the measure. In addition, hospital characteristics, such as the case mix of the patients, volume and teaching status, can influence readmission rates. The literature demonstrates that readmissions are a measure of healthcare utilization, and reducing avoidable readmissions reflects an improvement in hospital quality of care.

There are a number of studies that use hospital mortality rates as an indicator of quality of hospital care. For the purpose of this dissertation, mortality rates are defined as hospital patients who died within 30 days of discharge. These measures-- 30-day risk adjusted mortality rates for the Medicare population for certain conditions-- are publicly reported by CMS on the Hospital Compare website. In addition, the Affordable Care Act established the Hospital Value Based Purchasing Program, which adjusts a portion of Medicare hospital payment based on performance on a set of quality of care measures. Starting in 2014, 30-day mortality rates for certain conditions are included as part of the composite score in Medicare's Hospital Value

Based Purchasing Program to evaluate a hospital's performance, which demonstrates the importance of this measure to the Medicare program as an indicator of quality of care. This also demonstrates that mortality rates are a policy priority for Medicare.

There have been several studies that use mortality rates as an indicator of quality of care for hospitals. One study examined hospital patient satisfaction scores and how that compared to several health outcome indicators, including 30-day mortality rates for the Medicare FFS population. The study justified using the 30-day mortality rate because it represents the quality outcome domain in the Donabedian framework and it represents components of key national policy initiatives, including Medicare's Hospital Value Based Purchasing Program. The study found that hospital patient satisfaction scores were positively related to a lower perioperative mortality rate, when adjusted for hospital characteristics and volume (Tsai, 2015).

Another study examined the impact of the CMS Hospital Value Based Purchasing Program on 30-day mortality rates. More specifically, the study examined whether the payment penalties and bonuses applied to Medicare payments for hospitals based on their performance on a number of quality measures impacted 30-day mortality rates. The study found that three years after the introduction of the Hospital Value-Based Purchasing Program, there was no evidence that it has led to better patient outcomes. Specifically, the trends in mortality for the target conditions among hospitals participating in Hospital Value-Based Purchasing Program slowed after the program's introduction, although that slowing was also seen among hospitals not participating in the program. Furthermore, the study found that among hospitals with worse patient mortality at baseline, there was no evidence that the Hospital Value-Based Purchasing Program drove improvement as compared to a matched group of hospitals that were not subject to the Hospital Value-Based Purchasing Program (Burke, 2017). This study demonstrates both the use of mortality measures as a quality of care indicator and the value of assessing how changes in Medicare reimbursement impacts such quality of care.

Overall, a review of the literature has found that mortality rates are indicators of hospital quality of care and that reducing mortality rates is a policy priority for Medicare, which supports the use of these measures in this study.

Using Difference-in-Differences Methods in Health Policy Studies

As described in more detail in Chapter Three (Methods), this study intends to use several statistical analyses to evaluate hypotheses. In addition to multiple linear regression, a common technique, this study will use difference-in-differences statistical modelling to evaluate the hypotheses. The difference-in-differences method has been used in economic analysis and is becoming more frequently used in health policy evaluations. Difference-in-differences models partially address the limitations in linear regression modeling by using repeated cross-sectional data. Additionally, observational studies are commonly used to evaluate the changes in outcomes associated with health care policy implementation. However, a limitation in using observational studies in this context is the need to control for other factors related to those outcomes that could occur during that time. The difference-in-differences approach is increasingly applied for health policy evaluations to address this problem. The approach compares changes in the outcome in those places that have implemented a policy with changes in the outcome in those places with no policy. This approach removes trends over time in both intervention and comparison hospitals. It is then possible to conclude that significant changes in the outcome are associated with the new policy.

In difference-in-differences modeling, outcomes after and before the policy are compared between the comparison group without the exposure (group 1) and the study group with the exposure (group 2), and the difference is removed from the outcome in order to determine the specific impact of the policy on that outcome. Additionally, there are two differences in outcomes that are important: the difference after versus before the policy change in the group exposed to the policy (Group $2_{\text{current time}}$–Group 2_{baseline}) and the difference after versus before the date of the policy change in the unexposed group (Group $1_{\text{current time}}$–Group 1_{baseline}) The change in outcomes that are related to implementation of the policy beyond background trends can then be estimated from the difference-in-differences analysis as follows: (Group $2_{\text{current time}}$– Group 2_{baseline}) –(Group $1_{\text{current time}}$–Group 1_{baseline}). If there is no relationship between policy implementation and subsequent outcomes, then the difference-in-differences estimate would be equal to 0. Alternatively, if the policy is positively associated with a change in the outcome, then the outcomes following policy implementation will improve to a greater extent in the exposed group, as demonstrated by the difference-in-differences estimate. Regression modeling can be utilized in difference-in-differences methods in order to adjust by covariates, or identify interaction terms or to assess statistical significance (Dimmick, 2014). Studies have identified two common limitations of the difference-in-difference methods, which will also be described in Chapter 3 (Methods) for this study. First, utilizing difference-in-difference methods assumes that the trends in outcomes between the test group and comparison groups are the same prior to the policy intervention, sometimes referred to as the parallel trend assumption. If this assumption is true, then it is reasonable to assume that these parallel trends would continue for both groups in the absence of this policy. This assumption can be tested by examining the trends for both groups before the policy was implemented. If the trends are significantly different prior to the implementation of the policy, a difference-in-differences analysis could be biased and a different comparison group should be used. This study will utilize a similar test to determine if such a limitation exists. Second, the common shocks assumption assumes that an unexpected or unpredictable event unrelated to the policy that impacts the outcomes will do so the same extent for the test group and comparison group. A limitation to implementing the difference-in-differences design is finding a comparison or control group for which these assumptions are met (Dimmick, 2014).

There have been several recent studies that utilize the difference-in-differences method to evaluate the effects of Medicare payment policy over time. These studies described below share many similarities with the evaluation of Section 1109 in that they look at the impact of a change in Medicare payment policy over time on certain outcomes for healthcare providers or patients. While at the time of this literature review, there were 69 studies that met the search criteria of "difference-in-differences" and "Medicare", this section highlights a few studies that support the use of this method. One study examined the impact of an ACA provision that provided additional Medicare hospital payments to low volume hospitals for a specified period of time. The study examined the effect of the ACA payment adjustment on qualifying hospitals' profitability margins, and the hospital and market characteristics of the hospitals that would be most adversely affected by the loss of the ACA payment adjustment. The study utilized the difference-in-differences regression model with hospital-level random effects to determine whether the ACA low volume payment adjustment improved qualifying rural hospitals' profitability margins relative to rural hospitals not receiving the low volume payment adjustment. The study stated that difference-in-differences models were useful because they reduce bias stemming from selection into treatment and control groups by comparing each group relative to its respective time trend (Whitaker, 2016).

Another study examined the association between the 2014 Medicaid expansion established by the Affordable Care Act and hospitals' uncompensated care costs, Medicaid revenue, and financial margins utilizing difference-in-differences modeling. Difference-in differences statistical modeling was used to estimate changes in outcomes associated with the ACA. Separate models were estimated for each outcome measure and those models included hospital fixed effects, a set of fiscal year–specific dummy variables, and a random error term. Robust standard errors were clustered at the hospital level to correct for possible heteroscedasticity and autocorrelation (Blavin, 2016).

Finally, one study used difference-in-difference methods to evaluate the effects of Medicare's hospital pay-for-performance demonstration project on hospital revenues, costs, and margins and on Medicare costs. The study looked at hospitalizations for acute myocardial infarction (AMI) over time for hospitals that participated in a pay-for-performance demonstration compared to hospitals that did not participate in the demonstration. The study also utilized propensity score matching between the test hospitals and comparison hospitals based on certain hospital characteristics such as teaching status, average daily census and bed size. The outcome variables in this study were hospital revenues, costs, and margins and Medicare payments for AMI hospitalizations. Then the study used a difference-in-differences model to examine the effects of the Medicare pay-for-performance program on hospital revenues, costs, and margins and Medicare payments for these AMI hospitalizations. The results showed that changes in hospital financials associated with the pay-for-performance program were small and not statistically significant. Hospital revenues increased at pay-for-performance hospitals compared with comparison hospitals after the implementation of the pay-for-performance demonstration, but these increases were small in absolute and relative terms and were not statistically significant (Kruse, 2012).

The review of the literature suggests that the difference-in-differences method can be a useful technique to evaluate health policy studies when comparing changes in an outcome in places that have implemented a policy with changes in an outcome in those places with no policy. The study design presented in this dissertation is set-up in such a way that the difference-in-differences method could be used as part of the analysis and it is supported by the literature.

Using Propensity Score Matching to Evaluate Health Policy Interventions

As described in more detail in Chapter Three (Methods), this dissertation aims to use several statistical analyses to evaluate the hypotheses in this study. The study will utilize propensity score matching, which is a method used to reduce bias in observational studies by creating two populations that are similar across a number of covariates using a match on a propensity score. The matched samples can be considered as a quasi-experimental population.

The literature shows that propensity score matching is a technique used in health policy evaluations. One review study examined various statistical approaches to address common challenges of conducting policy evaluations including constructing a comparison population when a policy affects a population for whom a well-matched comparator is not immediately available (using propensity score or synthetic control approaches). This review study examined the literature and found that propensity score matching is an approach to form a comparator population for the policy-affected population and can be utilized when one is able to identify some who were exposed to a policy of interest and others who were not. However, propensity score matching is used when those unexposed differ from exposed subjects in obvious ways, such as in income status or location. The review study noted that a propensity score measures the estimated probability that individuals in a data set will experience policy exposure, given their observed features such as age, sex, income, and location. A propensity score is provided for each observation using logistic regression, in which the policy exposure is regressed against observed covariates of interest. The review study noted that a weakness of propensity score matching is that inferences from the approach can be made only when both policy-unaffected and -affected observations have nonzero probabilities of being in either group (Basu, 2017). One study used propensity score matching to examine the impact of paid and unpaid supplementary caregiving on preventable readmissions among Medicare home health beneficiaries with diabetes. Using Medicare claims data and other national datasets, the study used propensity score matching based on beneficiaries' "predisposing, enabling, and health need factors" to create matched cohorts for episodes solely assisted by paid supplementary caregivers versus those solely assisted by unpaid supplementary caregivers (or the intervention under evaluation). Using the propensity score, the study applied Cox regression on the matched cohorts to estimate the 30-day preventable readmissions for certain conditions (Chen, 2017). Another recent study used propensity score matching to evaluate a change in healthcare payment policy where it examined the association of health outcomes and medical spending with a bundled-payment pay-for-performance program for breast cancer in Taiwan compared with a fee-for-service (FFS) program. It was a patient level analysis that matched patients in the bundled-payment program with control individuals in the FFS program (Wang, 2017). While several studies have used propensity score matching to match at the patient level, the literature shows that there are studies that use propensity score matching at the hospital level, similar to this dissertation. One recent study examined the association of hospital enrollment and participation in the American College of Surgeons quality reporting program with outcomes and Medicare payments compared with control hospitals that did not participate in the program, using propensity score matching. The control hospitals were identified using propensity score matching, as compared to the hospitals enrolled in the quality reporting program. The propensity score match was done on certain outcome variables and surgical volume with a 1:2 level of matching for the study hospitals versus the control hospitals (Osborne, 2015).

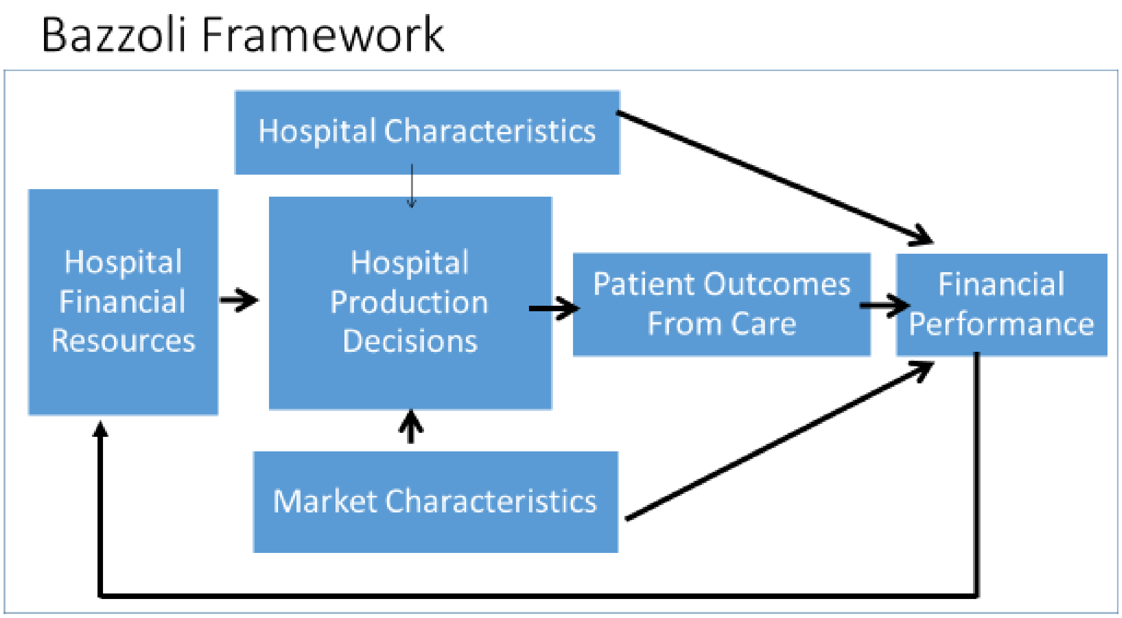
These are a few examples in the literature that demonstrate the use of propensity score matching as a technique to evaluate policy interventions which can be done at the hospital-level. The benefits of this technique are that it can reduce bias in observational studies by creating two populations that are similar across a number of covariates using a match on a propensity score. The literature also supports using the propensity score technique in evaluating the hypotheses of this study.

Chapter 3: Study Methods

Conceptual Framework

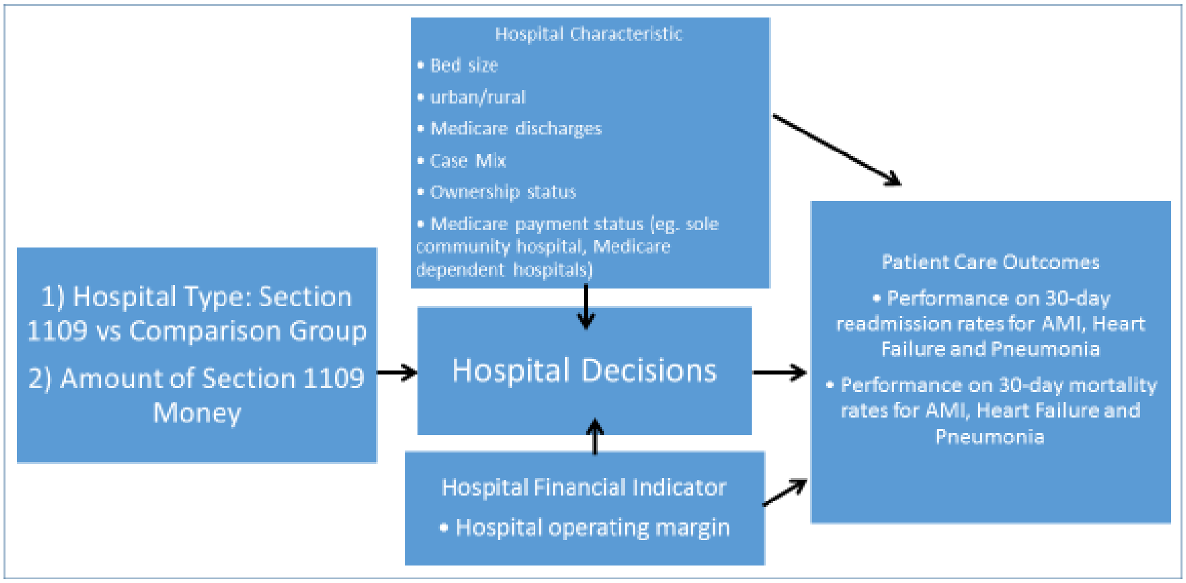
The conceptual framework that has influenced the framework for this study was developed by Bazzoli et al. to examine hospital financial conditions and quality of care (Bazzoli, 2008). This model examined the relationship among financial resources on hospital decisions and patient health outcomes and also accounted for the contribution of market characteristics and hospital characteristics on the patient health outcomes. That study examined how hospitals' decisions about the quality of their product can also be influenced by other institutional and market factors. Hospital characteristics, including ownership status, system affiliation, hospital bed size and patient characteristics, can influence the costs of producing a high-quality product. All of these characteristics, in turn, also influence future financial performance. Their study used the following conceptual framework which also serves as the basis of the framework for this study:

Figure 1: Bazzoli Framework and Conceptual Framework



The conceptual framework for the Bazzoli study is modified to apply to this investigation such that the framework examines how the infusion of additional funding under Section 1109 impacts a hospital's performance on readmission rates and mortality rates while taking into consideration hospital characteristics, market factors and financial indicators.

Conceptual Framework



Modeled after Bazzoli framework (Bazzoli, 2008)

Other conceptual frameworks were also examined in order to inform the conceptual framework used for this study. There are a variety of conceptual frameworks that have been utilized to examine the relationship of a hospital's reimbursement and quality of care. This body of work suggests that it may be important to consider the relationship between a hospital's financial condition and quality of care, as a hospital's financial condition can be a competing variable that affects how a hospital's Medicare reimbursement relates to quality of care. For example, an early study by Newhouse found behavior in which non-profit hospitals used the excess of payments over costs for those patient groups that were profitable in order to expand the quality and/or quantity of services they offered (Newhouse, 1973).

There have been some studies that examined the relationship between a hospital's financial condition and quality of care using a variety of conceptual frameworks. To briefly summarize the prevailing conceptual frameworks, there is first the Andersen Behavioral Framework that was originally designed to predict and explain use of health care services by individuals; this has recently been applied to model clinician response to quality-based payment incentives. The Andersen Behavioral Framework includes hospital characteristics and resources that motivate coordination of health services.

Another dominant conceptual framework is the Donabedian Quality Framework that is used to assess quality of care (Donabedian, 1966). The Donabedian Quality Framework examines the relationships among three related concepts--structure, process and outcomes. First, structures of health care are defined as the physical and organizational aspects of care settings (e.g., facilities, equipment, personnel, operational and financial processes supporting medical care, etc). Second, the processes of patient care are located in the middle of the diagram because they rely on the structures to provide resources and mechanisms for participants to carry out patient care activities. In addition, processes are performed in order to improve patient health care outcomes in terms of promoting recovery, functional restoration, survival and even patient satisfaction.

Study Questions and Hypotheses

This study begins with the general research questions: Do the acute care hospitals that have received bonus payments under Section 1109 of the Affordable Care Act, which are hospitals located in the quartile of counties with the lowest Medicare per beneficiary spending, provide equivalent quality of care, in terms of 30-day mortality rates and 30-day readmission rates, in comparison to other acute care hospitals? Did the hospitals that received Section 1109 funding show greater change in quality of care after receiving the funding compared to hospitals that did not receive funding? Did hospitals that received more money under Section 1109 show more change in their quality of care than Section 1109 hospitals that received less money?

The study seeks to evaluate the implementation of Section 1109 and whether funding was distributed to hospitals that provide high quality of care or whether the funding led to change in quality of care. The study tests the following null hypotheses:

H_{01}) Prior to the intervention, the hospitals that are located in areas with the lowest quartile of Medicare per beneficiary spending and received bonus payments under Section 1109 are not different compared to all other acute care hospitals, in terms of certain quality of care indicators, specifically, in terms of 30-day mortality rates and 30-day readmission rates.

H_{02}) The hospitals that received payments under Section 1109 had an equivalent change in quality of care in terms of changes in 30-day mortality rates and 30-day readmission rates, compared to hospitals that did not receive bonus payments under Section 1109, when comparing quality of care indicators before and after the Section 1109 hospitals received their bonus payments.

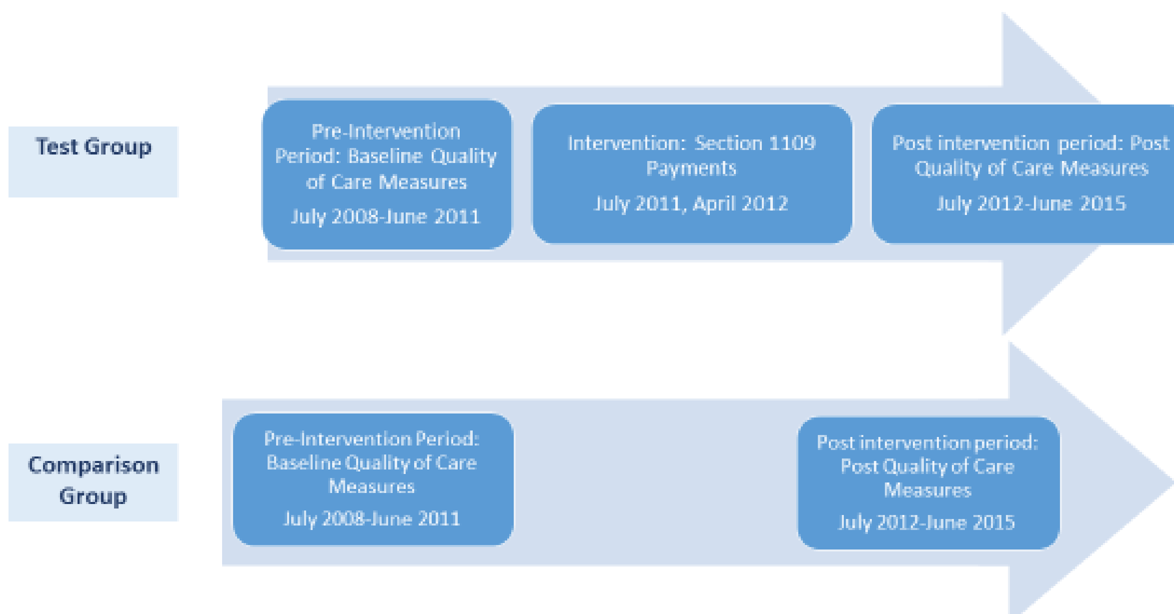
H_{o3}) The hospitals that received a greater amount of Section 1109 funding are not different in terms of the level of change in quality of care than hospitals that received less funding under Section 1109.

The study does not provide for alternative hypotheses. Given the inconsistent findings in the literature review on how payment relates to quality of care, if we reject the null hypothesis, we cannot determine whether the alternative hypothesis would be that the Section 1109 hospitals had better or worse quality of care, as compared to non-Section 1109 hospitals. Because we cannot assign directionality in the alternative hypotheses, we do not provide them for this study.

Study Design

This study is a natural experiment and a pre/post observational cohort study design where Section 1109 hospitals were given bonus money and the other hospitals were not given money over time. The intervention in this study is the bonus payments received by Section 1109 hospitals that occurred in July 2011 and April 2012. The pre-period in this study is July 2008 through June 2011 and the post-period is July 2012 through June 2015. The Campbell Stanley notation of this design is: Test: X 0 X; Comparison: X X. Figure 2 shows a timeline for this study:

Figure 2: Timeline of Study



The design of this study examines the group of hospitals that received the money under Section 1109, which were hospitals located in the bottom quartile of counties ranked for Medicare Part A and Part B spending per beneficiary. The analysis compares this group of hospitals to a comparison group of all other acute care hospitals that did not receive funding under Section 1109. For the purpose of this study, hospitals are defined as acute care hospitals paid under the IPPS. Only IPPS hospitals were eligible to receive bonus payments under Section 1109. Under this definition, hospitals that are not paid under the IPPS, including Critical Access hospitals, Long Term Care hospitals, Veteran's hospitals, Cancer hospitals, children's hospitals, and acute care hospitals in Maryland paid under a State waiver were not considered hospitals eligible for inclusion in this study.

The study compares specific quality indicators among the hospitals that received money under Section 1109 to the comparison group of hospitals, before and after the Section 1109 hospitals received their bonus payments. The baseline, or pre-intervention, quality indicators data are based on the readmission and mortality rates data posted on the CMS Hospital Compare Website, which is based on three years of claims data, spanning July 2008 to June 2011. This includes the time period before the Section 1109 hospitals received their funding. The comparison, or post-intervention, quality indicator data are based on 30-day readmissions and mortality rates data posted on the CMS Hospital Compare website based on a performance period of July 2012 to June 2015, which includes the time period after which the Section 1109 hospitals received their funding.

This is a retrospective cohort study in which we analyze existing Medicare claims and health outcomes data.

Description of Data Sources

The study uses several data sources. The list of hospitals that received money under Section 1109 is publicly available on the Centers for Medicare and Medicaid Services (CMS) website. This file identifies the hospitals located in the quartile of counties with the lowest

Medicare Part A and B spending per beneficiary, which is the test population for this study. This file also provides the Medicare provider number (or Hospital Identifier), and the name and county of the hospitals that received money under Section 1109. There are 400 hospitals that are in this test population that received money under Section 1109.

The data source used to determine the hospital characteristics is the FY 2011 Inpatient Prospective Payment System (IPPS) Impact File posted on the CMS website. The IPPS Impact File is a hospital-level file that contains hospital payment information and hospital characteristics used for Medicare hospital inpatient rate setting. The FY 2011 IPPS Impact File was produced in August 2010. This file contains Medicare information by hospital, including bed size, county location, rural or urban identification, teaching hospital status and Medicare case mix. This file merged with the list of qualifying hospitals is used to characterize the hospitals that received funding under this provision. The comparison group is non-Section 1109 hospitals. Those are all acute care hospitals paid under the IPPS that are not located in the quartile of counties with the lowest Medicare per beneficiary spending. There are 3100 hospitals in the comparison group. These hospitals and their characteristics are also identified from the FY 2011 IPPS Impact File.

The Medicare Hospital Cost Report was used to calculate the total hospital margins, a covariate in the study. Using the 2012 Medicare Hospital Cost Reports, total hospital margin was calculated as follows: $\frac{Net\ Income}{Net\ Patient\ Revenue + Total\ Other\ Income} = total\ hospital\ margin$

The Section 1109 hospitals are also categorized based on the relative amounts of bonus payments they received under the provision. The weighting factors or the proportion of the funding that each hospital received under Section 1109 is posted on the CMS website, so the share of the $400 million that each Section 1109 hospital received as bonus payments can be calculated.

Hospital quality of care indicators are measured in terms of 30-day mortality rates and 30-day readmission rates that are posted on the Hospital Compare Website. The Hospital Compare Website, managed by CMS, publicly reports the 30-day mortality rates and 30-day readmission rates by hospital for heart failure, AMI and pneumonia. Readmission rates and mortality rates for the Section 1109 hospitals are compared to all other acute care hospitals, both before and after the Section 1109 hospitals received their bonus payments.

In summary, the following data sources are used:

1. Section 1109 hospitals listed on the CMS website: Identifies test population
2. FY 2011 IPPS Impact File: Identifies comparison population and hospital characteristics for comparison and test populations.
3. Section 1109 Payment Factors on the CMS website: Identifies the bonus payments that the Section 1109 hospitals received.
4. 30-day readmission rates and mortality rates posted on the Hospital Compare Website.
5. 2012 Medicare Hospital Cost Report on the CMS website: Data reported on these forms were used to calculate each hospital's total hospital margin.

Creation and Cleaning the Data Set and Variables

Considerable effort was taken to pull data from the multiple data sources, scrub the data by comparing records across multiple data bases, ensuring no duplicate records to assure accuracy for this research. All of the data used in this study is stored as SAS files and all of the displayed data are summarized, aggregated data at the hospital level and no patient-level data was shared for the purposes of the study.

Study Population and Setting:

Variables

The independent variable, or the intervention in this study, is the implementation of Section 1109. The hospitals in the study are either categorized as benefitting from Section 1109 and receiving money from the provision or the hospitals are categorized as not receiving money from Section 1109. The hospitals that receive bonus payments under Section 1109, which are hospitals that are located in the lowest quartile of counties of Medicare Part A and Part B spending per beneficiary are the test group and the hospitals that do not receive money under Section 1109 are the comparison group. There are 400 hospitals in the test group and there are 3100 hospitals in the comparison group. For those hospitals in the test group, the amount of money received is also introduced as an independent variable in some analyses. In addition, during the analysis process, a consideration is made as to whether the size of the comparison group, which is currently at 3,100 hospitals, is too large. Thus, certain analyses were conducted with the comparison group to exclude hospitals based on certain hospital characteristics in order to be more comparable to the test population. As described in greater detail in Chapter 4 (Results), the comparison group was reduced to include hospitals of a similar bed size to the test group, and to include only the hospitals located in the same thirty-eight states as the test group. In addition, as discussed further in the analytical approach section, sub-analyses were conducted in which the study and comparison groups are matched as another method to control for certain hospital characteristics that may influence the outcome variables in this study.

The dependent variables of the study are the hospital's 30-day Medicare FFS readmissions rates and 30-day Medicare FFS mortality rates. The hospital's 30-day readmissions and mortality rates are based on the data posted on the CMS Hospital Compare website. The readmissions measures are hospital-specific, risk-standardized, 30-day all-cause readmission rates for Medicare fee-for-service (FFS) patients discharged from the hospital with a principal diagnosis of pneumonia or AMI or heart failure. To account for the clustering of observations within hospitals and differences in the number of admissions across hospitals, CMS uses hierarchical logistic regression to estimate risk-adjusted rates. The formula to calculate the readmission rate for each condition is as follows:

$$\frac{Hospital's\ Predicted\ Number\ Readmissions}{Hospital's\ Expected\ Number\ of\ Readmissions}\ x\ National\ Observed\ Readmission\ Rate$$

The “predicted” number of readmissions (the numerator) is calculated by regressing the risk factors identified for each condition, and the hospital-specific intercept on the risk of readmission. The estimated regression coefficients are then multiplied by the patient characteristics in the hospital. The results are then transformed and summed over all Medicare patients attributed to the hospital to get a value. The “expected” number of readmissions (the denominator) is obtained by regressing the risk factors identified for each condition and a common intercept on the readmission outcome using all hospitals in our sample. The estimated regression coefficients are then multiplied by the patient characteristics in the hospital. The results are then transformed and summed over all patients in the hospital to get a value. This ratio is multiplied by the national rate to calculate the risk standardized readmission rate (Grady et al, 2013).

The model uses administrative claims data from each index hospitalization, and from inpatient and outpatient Medicare claims from the 12 months prior to the hospitalization. The hospital specific mortality measures are risk adjusted based on patient characteristics such as age, gender and comorbidities. CMS first chose to focus their readmission measurement and reduction efforts on three conditions: heart failure, pneumonia and AMI, as these represent high volume and high cost cases. CMS defines certain exclusions for readmissions in their measures including if a patient is transferred to another hospital, if the patient dies during the initial admission or if the patient left the hospital against medical advice. In addition, certain planned readmissions, developed through an algorithm by CMS, are not considered readmissions in these measures. For the baseline readmission rates in this study, the measure is based on three years of claims data from July 1, 2008 to June 30, 2011. For the comparison readmission rates in this study, the measure is based on a three year performance period from July 1, 2012 to June 30, 2015. The measures are based on three years of data in order to ensure that there are a sufficient number of cases to have a reliable measure. The minimum number of cases to calculate the measures is 25 cases, which can be met using three years of data.

Similar to the 30-day readmission rate, the 30-day Medicare FFS mortality rate is a risk-adjusted measure examining hospital rates for Medicare fee-for-service beneficiaries' deaths within 30 days of discharge. To account for the clustering of observations within hospitals and differences in the number of admissions across hospitals, CMS uses hierarchical logistic regression to estimate risk-adjusted rates. The formula to calculate the mortality measure for each condition is as follows:

$$\frac{\text{Number of deaths within 30 days predicted on the basis of the hospital's performance with its observed case mix}}{N\text{umber of deaths expected on the basis of the nation's performance with that hospital's case mix}}\ x \text{ national observed mortality rate}$$

The "predicted" number of deaths (the numerator) is calculated by regressing the risk factors identified specific for each condition and the hospital-specific intercept on the risk of mortality. The estimated regression coefficients are then multiplied by the patient characteristics in the hospital. The results are then transformed and summed over all patients attributed to the hospital to get a value. The "expected" number of deaths (the denominator) is obtained by regressing the identified risk factors and a common intercept on the mortality outcome using all hospitals in our sample. The estimated regression coefficients are then multiplied by the patient characteristics in the hospital. The results are then transformed and summed over all patients in the hospital to get a value. This ratio is multiplied by the national rate to calculate the risk standardized mortality rate for each condition (Grady et al, 2013).

The model uses administrative claims data from each index hospitalization, and from inpatient and outpatient Medicare claims from the 12 months prior to the hospitalization. The hospital-specific mortality measures are risk adjusted based on patient characteristics such as age, gender and comorbidities. CMS first chose to measure mortality rates for three conditions: heart failure, pneumonia and AMI. Similar to the readmission measures, the minimum number of cases required to calculate a measure is 25 cases. For this study, the baseline mortality measures are based on three years of claims data from July 1, 2008 to June 30, 2011 and the comparison mortality measures are based on three years of claims data from July 1, 2012 through June 30, 2015.

In summary, in order to demonstrate whether hospitals showed any change in quality of care, in terms of 30-day readmission rates and 30-day mortality rates, the analysis evaluates these measures prior to receiving the Section 1109 funding and after receiving the funding. CMS reports 30-day readmission rates and 30-day mortality rates over three years, so the analysis evaluates the 30-day readmission rates and 30-day mortality rates from 2008 to 2011 as the baseline and the 30-day readmission rates and 30-day mortality rates from 2012 to 2015 for the post-intervention period.

Methods of Data Collection

The data sets described in the Study Design section are secondary data sources that are maintained by CMS. All of the data sources are publicly available on the CMS website or CMS Hospital Compare website.

As discussed earlier, the study uses patient data to the extent that it is included in the readmissions and mortality measures. Because this is a national data set administered by the federal government, measures have been taken to ensure the privacy and confidentiality of the health data. We cannot identify who is a participant from the data.

Below is a table summarizing the variables to be used in this study, whether or not they represent an independent, dependent or control variable, whether the value of the variable is continuous or dichotomous, the data source, the unit of measurement, and the time period of the data collection. The last column cites previous studies in which similar variables have been used, which provides support for the use of these variables in this study. The 30-day risk adjusted readmission rates and 30-day risk adjusted mortality rates have been used in previous studies as indicators of quality of care for a hospital. The hospital characteristics that are covariates in this study have also been used in previous studies.

Table 2: Summary of Study Variables

Variable	Independent/ Dependent/ Control	Continuous/ Dichotomous	Data Source	Unit of Variable	Time Period	Study
Hospital Type: Section 1109 Hospital vs. Other Acute Care Hospital	Independent	Dichotomous	CMS provider list from FY 2009; Section 1109 provider list from FY 2009	Dummy variable indicating yes or no for Section 1109 status	FY 2009	
Section 1109 Money Received by Hospital	Independent	Continuous	Section 1109 provider list from FY 2009	Expressed as dollar amount, logarithm of dollar amount, dollar amount per number of inpatient beds, logarithm of dollar amount per number of inpatient beds	Payments published in FY 2010, payments made on July 2011 and April 2012	
30 Day Hospital Readmission Rates for AMI, Heart Failure, Pneumonia	Dependent	Continuous	CMS Hospital Compare website	Ratio of Predicted Readmission versus Expected Readmission multiplied by the national rate	July 2008 June 2011; July 2012-June 2015	Gilstrap, 2014
30 Day Hospital Mortality Rates for AMI, Heart Failure, Pneumonia	Dependent	Continuous	CMS Hospital Compare website	Ratio of Predicted Mortality versus Expected Mortality multiplied by the national rate	July 2008-June 2011; July 2012-June 2015	Romley, 2013; Tsai, 2015
Percentage Point Change in the 30-day readmission rates for AMI, Heart Failure, Pneumonia	Dependent	Continuous	CMS Hospital Compare website	The percentage point difference in the Readmission Rate in the post period and the baseline period		
Percentage Point Change in the 30-day mortality rates for AMI, Heart Failure, Pneumonia	Dependent	Continuous	CMS Hospital Compare website	The percentage point difference in the Mortality Rate in the post period and the baseline period		
Bed size	Control	Continuous	IPPS Impact Table	Number of Hospital Inpatient Beds, also expressed as the logarithm of the number of inpatient beds	FY 2011	Borah, 2012
Medicare Case Mix	Control	Continuous	CMS Case Mix Index Table based on Medicare Inpatient Claims Data	Average of the Medicare MS-DRG relative weights	FY 2011	Bazzoli, 2003
Total Hospital Margin	Control	Continuous	Medicare Hospital Cost Reports	Percentage of Net Income out of Net Patient Revenue and Other Income	2012	
Sole Community Hospital	Control	Dichotomous	IPPS Impact Table	Dummy variable indicating yes or no for Sole Community Hospital status	FY 2011	
Medicare Dependent Hospital	Control	Dichotomous	IPPS Impact Table	Dummy variable indicating yes or no for Medicare Dependent Hospital Status	FY 2011	

Ownership Status: For Profit, Government, non-profit	Control	Dichotomous	IPPS Impact Table	Dummy variable indicating for-profit, government or non-profit status	FY 2011	
Rural vs. Urban	Control	Dichotomous	IPPS Impact Table	Dummy variable indicating rural or urban	FY 2011	
State	Control	Dichotomous	IPPS Impact Table	Dummy variable for state that hospital is located in	FY 2011	
Number of Medicare FFS Discharges	Control	Continuous	IPPS Impact Table	Number of annual Medicare FFS discharges, also expressed as the logarithm of Medicare FFS discharges	FY 2011	Romley, 2013
Number of Medicare FFS Discharges for each outcome condition- AMI, Heart Failure, Pneumonia	Control	Continuous	CMS Hospital Compare website	Number of condition specific Medicare FFS discharges used to calculate the baseline readmission rate or mortality rate	July 2008-June 2011	

Analytical Approach

The data used in this analyses are quantitative data for two time periods (pre-intervention and post-intervention) and the variables in this study are continuous and dichotomous. As such, a variety of statistical models are used to determine whether any differences exist in the dependent variables for hospitals that received funding under Section 1109 and hospitals that did not. In other words, the statistical model is used to determine whether hospitals that are located in counties with the lowest Medicare spending are different or not with respect to health outcomes in comparison to hospitals located in counties with higher Medicare spending. This study uses individual multiple linear regression analyses to determine the relationship between the independent variable and the six outcome variables (three mortality measures, three readmissions measures. The model controls for the number of Medicare discharges, bed size, Medicare case mix, rural versus urban status, total hospital margin, ownership status, Medicare Dependent Hospital status and sole community hospital status. These variables are identified as control variables in this analysis because, based on the information presented in Table 4 below, these characteristics differ between the test hospitals and the comparison hospitals. This study seeks to ensure that these characteristics do not influence the outcomes, rather these effects are removed in assessing the relationship of the independent variables and the outcome dependent variables. The dependent variables, the 30-day readmission rates and 30-day mortality rates, are highly adjusted. The risk adjustments for these variables are age, gender and several comorbidities. As a result, this approach eliminates the need to use these patient specific covariates in the study and limits the covariates to hospital level characteristics. If the hospital does not have the minimum number of cases to calculate the quality of care indicator, according to the CMS measure specifications, then the hospital's observation is excluded from the analysis. Because this study is comprised of the entire IPPS hospital population and not a sample of hospitals, power calculations are not necessary. The data are analyzed using SAS.

Analysis for Hypothesis 1

The first hypothesis of this study is that hospitals that are located in areas with low Medicare per beneficiary spending provide quality of care that is equivalent to all other hospitals, in terms of mortality rates for AMI, heart failure and pneumonia and readmission rates for AMI, heart failure and pneumonia. To test this hypothesis, a t-test analysis is first performed to determine if there are statistically significant differences in the quality of care indicators for Section 1109 hospitals as compared to non-Section 1109 hospitals. Second, a multivariate linear regression is performed with covariates including bed size, Medicare case mix, number of Medicare FFS discharges, number of Medicare FFS discharges for the quality of care indicator, rural versus urban status, sole community hospital status, ownership status treated as a dummy variable (for profit versus government owned versus non-profit), total hospital margin. States are also treated as dummy variables in the analysis. The quality of care indicators under consideration are the dependent variables. The multivariate linear regression analysis is performed to examine if there are any statistically significant differences in each of the quality of care measures for the Section 1109 hospitals compared to the non –Section 1109 hospitals before the Section 1109 hospitals received additional funding.

An example equation for this model is as follows:

30-day readmission rate for AMI= b_0 + b_1(log bed size) + b_2(case mix) + b_3 (log Medicare discharges) +b_4 (rural/urban dummy) +b_5 (SCH dummy) + b_6 (MDH dummy) + b_y (ownership status dummy) + b_8 (State dummy) + b_9 (total hospital margin) + b_{10} (Section 1109 dummy) + error

Analysis for Hypothesis 2

The second hypothesis of this study is that hospitals that received payments under Section 1109 had an equivalent change in quality of care in terms of a change in 30-day mortality rates and 30-day readmission rates under Section 1109. There are four statistical approaches that are used to test this hypothesis. First, a t-test analysis is performed to determine if there are statistically significant differences in the change in the quality of care indicators for Section 1109 hospitals as compared to non-Section 1109 hospitals. Second, a multivariate linear regression is performed with covariates of bed size, Medicare case mix, number of Medicare FFS discharges, number of Medicare FFS discharges for the quality of care indicator, rural versus urban status, sole community hospital status, ownership status treated as a dummy variable (for profit versus government owned versus non-profit) and total hospital margin. States are also treated as a dummy variable. As later described in Chapter 4 on results, because we reject the first null hypothesis of the study for some of the dependent variables, the baseline performance on 30-day readmission rates and 30-day mortality rates are also included as a control variable. In other words, because the Section 1109 hospitals and the non-Section 1109 hospitals do show statistically significant differences in performances on 30-day mortality rates and 30-day readmission rates, that may bias the extent to which these quality of care indicators change over time for the Section 1109 hospitals compared to the comparison group of hospitals. The dependent variables are the percentage point change in the quality of care measures, comparing the quality of care measures before the Section 1109 hospitals received their funding and after the Section 1109 hospitals received their funding (or Outcome Variable $_{\text{Time 2}}$- Outcome Variable $_{\text{Time 1}}$). Specifically, the dependent variables are the percentage point changes in the 30-day readmission rates for AMI, Heart Failure and Pneumonia and the percentage point changes in the 30-day mortality rates for AMI, Heart Failure and Pneumonia from the baseline period of July 2008-June 2011 to the comparison period of July 2012-June 2015.

An example equation for this model is as follows:

Percentage point change in readmission rate for AMI= = b_0 + b_1(log bed size) + b_2(case mix) + b_3 (log Medicare discharges) +b_4 (rural/urban dummy) +b_5 (SCH dummy) + b_6 (MDH dummy) + b_y (ownership status dummy) + b_8 (State dummy) + b_9 (total hospital Margin) + b_{10} (baseline readmission rate for AMI)+b_{11} (Section 1109 status dummy) + error

A weakness with the multivariate linear regression model is that it assumes that changes in the outcome are solely attributable to the Section 1109 policy and the covariates in the study when there could be other factors occurring during this time period that are influencing the outcome. Ideally the comparison hospitals would be the same as the Section 1109 hospitals in everything other than the Section 1109 payments. However, in reality, differences, absent the Section 1109 policy, do exist between the study population and the comparison group. To overcome this potential weakness, the difference-in-differences model is also used to test this hypothesis. Using the difference-in-differences analysis, it assumes that absent the implementation of Section 1109, the difference in the quality of care between the study population and the comparison group would be the same over time. This technique is commonly used in evaluation of the impacts of policy or natural experiments, and similar policy evaluations described in the literature review use this technique. The differences between the Section 1109 hospitals and the comparison hospitals are not important in this model, but rather, the differences in the changes over time, as examined in the analysis. Instead of comparing outcomes between the Section 1109 hospitals and comparison groups after the intervention, the difference-in-differences method compares trends between the Section 1109 hospitals and comparison groups. The trend for an individual is the difference in the outcome for that individual before and after the intervention. In this case, the independent variable is whether or not the hospital received Section 1109 funding. The dependent variables are the differences in 30-day readmission rates and 30-day mortality rates.

An example equation for this model is as follows:

y_{jt}=b_0 + b_1*(t) + b_2*(j) + b_3*(t*j)+ b_4(log bed size) + b_5(case mix) + b_6 (log Medicare discharges) +b_7 (rural/urban dummy) +b_8 (SCH dummy) + b_9 (MDH dummy) + b_{20} (ownership status dummy) + b_{22} (State dummy) + b_{23} (total hospital Margin) + error

where Y_{jt} is the outcome variable; j is the Section 1109 hospital status dummy (Section 1109 hospitals have a dummy variable of 1 in both the baseline and comparison period); t is the dummy variable for the year (0 is for the baseline period and 1 is for comparison period).

A limitation of the difference-in-differences model is that any factor that disproportionately affects one of the two groups over the time period of the study and is not taken into account in the regression can invalidate or bias the estimate of the impact of the Section 1109 payment on changes in quality of care.

The fourth method we use to evaluate this hypothesis is propensity score matching, in which study hospitals and comparison hospitals are assigned probabilities that the hospital is a Section 1109 hospital (or propensity score) based on the observed values of its characteristics (the covariates). This score is a number between 0 and 1 that summarizes the influence of all of the observed characteristics on the likelihood of a hospital being a Section 1109 hospital. The equation for the propensity score is:

$e_i = Pr(Z_i = 1|X_i)$ or probability that observation is in treatment group given baseline covariates

e_i = propensity score

Z_i= observation

X_i = covariate

We use the following three propensity score methods in our analysis: 1) Inverse Probability of Treatment Weighting Method, 2) Stratification Method, 3) Matching, which were identified through a paper by Austin (Austin, 2011).

For the Inverse Probability of Treatment Weighing Method, we compute weights for each observation based on its propensity score and use it in further analysis. The weights create a synthetic sample in which the distribution of the baseline covariates is independent of treatment assignment. The weight for the Section 1109 hospitals are defined as follows:

$$\frac{Section\ 1109\ hospital\ observation}{propensity\ score\ weight\ for\ Section\ 1109\ observation} = weight$$

The weights for the comparison hospitals are as follows:

$$\frac{1 - Section\ 1109\ hospital\ observation}{1 - propensity\ score\ weight\ for\ Section\ 1109\ observation} = weight$$

A subject's weight is equal to the inverse of the probability of receiving the treatment that the subject actually received. Once the weights have been assigned to each observation, we use that to conduct simple linear regressions.

Under the Stratification Method, we rank hospitals by their propensity score and then group Section 1109 hospitals and comparison hospitals into quintiles based on propensity scores. Stratifying based on quintiles is used because it has previously shown that it eliminates 90% of bias due to continuous confounding variable (Cochran, 1968). Within each propensity score stratum, Section 1109 hospitals and comparison hospitals are expected to have comparable propensity scores. We then estimate the mean difference between the dependent variables for the Section 1109 hospitals and the comparison hospitals within each strata. We can also average the mean differences across the strata to produce an overall mean difference. In order to produce the overall mean difference to assess the overall difference between Section 1109 hospitals and non-Section 1109 hospitals, the stratum-specific estimates of effect are weighted by the proportion of hospital observations within that stratum or quintile.

Lastly under the matching procedure method, for each Section 1109 hospital, we find one or more matching comparison hospitals based on their propensity scores. The propensity score matching method tries to mimic the randomized assignment to treatment and comparison groups by choosing for the comparison group those hospitals that have similar propensities to the Section 1109 hospitals. We use the matched sample to do a t-test analysis to determine the treatment effect. More specifically, we used the following steps for the propensity score matching:

1. Specified set of confounding variables that might be related to both the treatment assignment and the outcome which are the Medicare case mix, total hospital margin from 2012, bed count, number of Medicare discharges, rural status, Medicare dependent hospital status, sole community hospital status, for-profit ownership and government hospital ownership.

2. Use this set variables to fit a regression model and compute propensity scores. The propensity score represents the probability of assignment to being a Section 1109 hospital (treatment group). We first perform logistic regression analysis using Section 1109 hospitals assigned a value of 1 and 0 otherwise as dependent variable, and the confounding variables identified in step 1 as independent variable. The probability being a hospital selected for the Section 1109 payment is calculated from the logistic regression analysis and is the propensity score for that hospital.

3. Specify the matching statistic or caliper (the distance metric for comparing the similarity of subjects) at 0.1 and the method for creating matched sets of observations.

4. Assess the balance of variables by comparing the distributions between the Section 1109 hospitals and comparison hospitals.

5. To improve the balance, repeated the process with a different set of variables for the logistic regression model, a different set of matching criteria, or a different matching method.

6. Use the output of the propensity match to run the t-test regression analyses with the Section 1109 hospitals and comparison hospitals identified through the propensity match.

The advantages of a matching approach are that it can reduce confounding and potentially increase efficiency. A weakness of the approach is that it assumes that those factors by which the study and comparison hospitals are matched upon are the only factors that affect the outcome variable. Furthermore, the effects of those matching variables on the outcome variables cannot be included in the model.

Analysis for Hypothesis 3

The third hypothesis is that hospitals that received a higher proportion of Section 1109 funding are not different in terms of improvement in quality of care than hospitals that received less funding under Section 1109. To test this hypothesis, Pearson and Spearman correlations are conducted. In addition, a multivariate linear regression is performed to examine the relationship of the independent variable of the amount of money received and the change in the dependent variables, including the mortality measured and readmissions measures prior to and after the Section 1109 payment with covariates of bed size, number of Medicare FFS discharges, number of Medicare FFS discharges for the quality of care indicator, total hospital margin, Medicare case mix, rural versus urban status, Medicare Dependent Hospital status, sole community hospital status and ownership status (proprietary status, government status). The independent variable is the amount of money received by the hospital expressed as the logarithm of the total amount of funding the hospital received or as the logarithm of the amount of money received per bed count. The dependent variables are the percentage point changes in the quality of care measures, comparing time period before the Section 1109 hospitals received their funding to after the Section 1109 hospitals received their funding. Specifically, the dependent variables are the percentage point changes in the 30-day readmission rates for AMI, Heart Failure and Pneumonia and the percentage point changes in the 30-day mortality rates for AMI, Heart Failure and Pneumonia from the baseline period of July 2008-June 2011 and the comparison period of July 2012-June 2015. An example equation is as follows:

Percentage point change in readmission rate for AMI= = b_0 + b_1(log bed size) + b_2(case mix) + b_3 (log Medicare discharges) +b_4 (rural/urban dummy) +b_5 (SCH dummy) + b_6 (MDH dummy) + b_y (ownership status dummy) + b_8 (State dummy) + b_9 (total hospital margin) + b_{10} (baseline readmission rate for AMI)+b_{11} (Section 1109 money) + error

As part of the analysis using multivariate linear regressions to test the three hypotheses in this study, a residual analysis is conducted to determine if a linear regression is the appropriate model or if nonlinear regression analyses should be considered.

Lastly, to overcome the weaknesses in the multiple linear regression model described earlier, a difference in differences model is used to assess this hypothesis. The equation for this model is as follows:

The equation for this model is as follows:

y_{jt}=b_0 + b_1*(t) + b_2*(j) + b_3*(t*Section 1109 payment)+ b_4(log bed size) + b_5(case mix) + b_6 (log Medicare discharges) +b_7 (rural/urban dummy) +b_8 (SCH dummy) + b_9 (MDH dummy) + b_{20} (ownership status dummy) + b_{22} (State dummy) + b_{23} (total hospital margin) + error

where Y_{jt} is the outcome variable; j is the dummy variable for Section 1109 status; t is the year dummy variable where it is 0 in the baseline period and 1 in the comparison period.

The distributions of the outcome variables are also examined and are described in Chapter 4 (Results), and the distributions of the outcome variables were not significantly skewed. If the distributions of the outcome variables were skewed, it would suggest that the data were not normally distributed and that may invalidate results from the models used to evaluate the data. Skewed data would suggest that the mean and standard deviation statistics are not informative of the spread of the data and would suggest that the multivariate linear regression model may not be a valid model to evaluate the relationships between the independent and outcome variables. If the data have skewed distributions, the logarithms of the outcome variables could be examined to determine if they have more normal distributions. If the logarithms of the outcome variables have more normal distributions, the models described above could be regressed on the logarithms of the outcome variables. However, based on the results of the distributions of the outcome variables that showed that the data were not skewed, we used the multivariate linear regression models and we did not use logarithms of the outcome variables.

Table 3: Summary of Analysis Plan

Hypothesis	Model	Weaknesses	Other Considerations
Hypothesis 1: Hospitals that are located in areas with low Medicare per beneficiary spending provide care equivalent to all other hospitals, in terms of mortality rates for AMI, heart failure and pneumonia and readmission rates for AMI, heart failure and pneumonia	A multivariate linear regression, with covariates including bed size, number of Medicare FFS discharges, number of Medicare FFS discharges for the quality of care indicator, total hospital margin, Medicare case mix, rural versus urban status, Medicare Dependent Hospital status, sole community hospital status and ownership status (proprietary status, government status, non-profit status).	May not be a valid model if the outcome variables are highly skewed.	Use logarithm of outcome variables as the dependent variables in evaluation, if data are highly skewed.
Hypothesis 2: Hospitals that received payments under Section 1109 had an equivalent change in quality of care in terms of a change in 30-day mortality rates and readmission rates, compared to hospitals that did not receive bonus payments under Section 1109.	A multivariate linear regression, with covariates of bed size, number of Medicare FFS discharges, number of Medicare FFS discharges for the quality of care indicator of interest, total hospital margin, Medicare case mix, rural versus urban status, baseline performance on the readmission rate or mortality rate of interest, Medicare Dependent Hospital status, sole community hospital status and ownership status (proprietary status, government status, non-profit status). Dependent variables are the percent change in the quality of care measures, comparing the quality of care measures before the Section 1109 hospitals received their funding and after the Section 1109 hospitals received their funding	Assumes that changes in the outcome are solely attributable to the Section 1109 policy when there could be other factors occurring during this time period that are influencing the outcome. Would not be a valid model if the outcome variables are highly skewed.	Difference-in-difference model where the independent variable is the Section 1109 status and the dependent variables are the changes in 30-day readmission rates and 30-day mortality rates before and after the qualifying hospitals received the Section 1109 funding. Having the outcome variables reflect the change in the readmission rates or mortality rates, removes biases between the treatment and comparison group due to permanent differences in the two hospital categories or due to time. Propensity score analysis with Section 1109 hospitals and comparison hospitals are matched on the covariates. This assumes that those factors by which the cases and controls are matched upon are the only factors that affect the outcome variable
Hypothesis 3: Hospitals that received a higher proportion of Section 1109 funding are not different in terms of improvement in quality of care than hospitals that received less funding under Section 1109	Multivariate linear regression is performed to examine the relationship of the independent variable of the amount of money received per bed size and the change in the dependent variables, including the mortality measures and readmissions measures prior to the Section 1109 payment with covariates of bed size, number of Medicare FFS discharges, number of Medicare FFS discharges for the quality of care indicator of interest, baseline performance on the readmission rate or mortality rate of interest, total hospital margin, Medicare case mix, rural versus urban status, Medicare Dependent Hospital status, sole community hospital status and ownership status (proprietary status, government status, non-profit status).	Would not be a valid model if the outcome variables are highly skewed.	Use logarithms of outcome variables as the dependent variable in evaluation, if data are highly skewed. Difference-in-difference model where the independent variable is the amount of Section 1109 funding that hospitals received and the dependent variables are the differences in 30-day readmission rates and 30-day mortality rates before and after the qualifying hospitals received the Section 1109 funding. Having the outcome variables reflect the change in the readmission rates or mortality rates, removes biases between the treatment and comparison group due to permanent differences in the two hospital categories or due to time.

Human Subject Issues

In August 2015 the Institutional Review Board Office at Johns Hopkins University determined upon review of the submitted IRB Office Determination Request Form for the dissertation titled Evaluation of Section 1109, that the research is not human subjects research.

Chapter 4: Results

Results of Descriptive Statistics Analysis

An exploratory data analysis was conducted comparing the test and comparison populations. Below are summary statistics on the Section 1109 hospitals and the other acute care hospitals in the comparison group.

Table 4 shows that the hospitals that benefitted from Section 1109 tended to be more rural than all other IPPS hospitals. The average bed size for Section 1109 hospitals was smaller compared to IPPS hospitals. Section 1109 hospitals were comparable to IPPS hospitals in terms of their teaching status and whether they received a Medicare Disproportionate Share hospital add-on payment. Section 1109 hospitals were more likely to be Sole Community Hospitals, which is a Medicare hospital categorization for hospitals that are located in rural areas that are a certain distance from other hospitals.

Table 4: Hospital Characteristics from FY 2011 IPPS Impact File

Hospital Characteristic	Section 1109 Hospitals	Comparison IPPS Hospitals
Number of Observations	400	3100
Rural	49%	24%
Urban	51%	76%
Average Bed Size	137 beds (min 4, max 716, std dev 124)	193 beds (min 1, max 1928, std dev 184.81)
Teaching Hospital	28%	30%
Receives Medicare DSH Payments	83%	79%
Sole Community Hospital	30%	9%
Medicare Dependent Hospital	7%	5%
Rural Referral Center	6%	8%
Indian Health Service Hospital	1%	1%
Ownership Status	70% % Non-Profit 15% For-Profit 15% Public	57% Non-Profit 26% For-Profit 17% Public
Average Medicare FFS Cases for One Year	2202 (min 1, max 12609, std dev 2203)	3107 (min 1, max 37713, std dev 3178)
Average Medicare FFS Cases for AMI over Three Year Period (2008-2011)	131 (min 1, max 1384, std dev 176.4)	161 (min 1,max std dev 1652,211)
Average Medicare FFS Cases for Heart Failure Over Three Year Period (2008-2011)	253 (min 1,max 1853, std dev 241.3)	379 (min 1, max 3667, std dev 359.1)
Average Medicare FFS Cases for Pneumonia Over Three Year Period (2008-2011)	245 (min 1, max 1256, std dev 179.1)	297 (min 1, max 2233, std dev 233.2)
Average Medicare Case Mix	1.4424 (min 0.563, max 2.3488, std dev 0.303)	1.46 (min 0.634, max 3.71, std dev 0.330)
Average Wage Index	0.94869 (min 0.7071, max 1.4448, std dev 0.125)	0.98056 (min 0.3963, max 1.9343, std dev 0.2032)
Average DSH Patient Percentage	25% (min 1.1%, max 82.6%, std dev 12.12%)	29% (min 0, max 119%, std dev 18.31%)
Hospital Total Margin 2012	5.46% (min -58%, max 47%, std dev 10.8%)	3.13% (min -1184%, max 71%, std dev 26)

Table 4 shows that in terms of Medicare payment characteristics, Section 1109 hospitals are, on average, comparable to other IPPS hospitals. Section 1109 hospitals have similar Medicare case mix as other IPPS hospitals, which shows that both groups of hospitals treat similar types of Medicare patients with comparable acuities of illness. The average wage index, which is the geographic adjustment applied to an IPPS and OPPS hospital payment that reflects the wages of the area of the hospital, differs for the two categories of hospitals. The DSH patient percentage is a measure of the hospital's low income patient population defined as the proportion of the hospital's Medicare patients who have Supplementary Security Income and the hospital's proportion of patients eligible for Medicaid. Section 1109 hospitals and other IPPS hospitals have comparable low income patient populations. Total hospital margins are higher for Section 1109 hospitals than the comparison group. Lastly, Section 1109 hospitals tend to have non-profit ownership status while the comparison hospitals were a mix of non-profit and for-profit ownership.

As shown in Table 4, the non- Section 1109 hospitals are different from the Section 1109 hospitals in that they are larger with respect to bed size and volume, and they are more urban. There is a potential that these factors can contribute to how hospitals perform on the quality of care indicators and it may not be appropriate for the comparison group to include these large hospitals. As a result, we modified our data set to remove hospitals with beds greater than 717 because the largest Section 1109 hospital has 717 beds. That exclusion results in 400 Section 1109 hospitals continuing to remain and 3029 non-Section 1109 comparison hospitals remaining in the data set. We then applied an exclusion to both remove hospitals with beds greater than 717 and hospitals located in the states that do not have Section 1109 hospitals. That exclusion results in 400 Section 1109 hospitals continuing to remain and 2362 non-Section 1109 comparison hospitals remaining. The following tables show the summary statistics for the trimmed data sets.

Table 5: Summary Statistics for Hospitals with < 717 Beds, and Hospitals <717 in States with Section 1109 Hospitals

Hospital Characteristic	For Hospitals with < 717 Beds		For Hospitals with <717 Beds Located in States with Section 1109 Hospitals	
	Section 1109 Hospitals- avg (min, max, std dev)	Comparison IPPS Hospitals- avg (min, max, std dev)	Section 1109 Hospitals- avg (min, max, std dev)	Comparison IPPS Hospitals- avg (min, max, std dev)
Number of Observations	400	3029	400	2362
Rural	49%	25%	49%	27%
Urban	51%	75%	51%	73%
Average Bed Size	137 beds (min 4, max 716, std dev 124)	175 beds (min 1, max 709, std dev 143)	137 beds (min 4, max 716, std dev 124)	170 beds (min 1, max 709, std dev142)
Average Number of Annual Medicare FFS Discharges	2202 (1, 12609, 2203)	2863 (1, 16520,,2623)	2202 (1, 12609, 2203)	2732 (1, 16520, 2568)
Teaching Hospital	28%	29%	28%	29%
Receives Medicare DSH Payments	83%	79%	83%	80%
Sole Community Hospital	30%	11%	30%	12%
Medicare Dependent Hospital	7%	6%	7%	6%
Rural Referral Center	6%	5%	6%	6%
Indian Health Service Hospital	1%	1%	1%	1%
Ownership Status	70% % Non-Profit 15% For-Profit 15% Public	55% % Non-Profit 28% For-Profit 16% Public	70% % Non-Profit 15% For-Profit 15% Public	57% Non-Profit 26% For-Profit 17% Public
Average Medicare Case Mix	1.4424 (0.563, 2.3488, 0.303)	1.45 (0.634, 3.71, 0.327)	1.4424 (0.563, 2.3488, 0.303)	1.456 (0.634, 3.71, 0.334)
Average Wage Index	0.94869 (0.7071, 1.4448, 0.125)	0.98024 (0.3963, 1.9343, 0.2045)	0.94869 (0.7071, 1.4448, 0.125)	0.9873 (0.707, 1.75, 0.1928)
Average DSH Patient Percentage	25% (1.1%, 82.6%,12.12)	29% (0, 119%, 18.38)	25% (1.1%, 82.6%,12.12)	29% (0%,119%,19)
Hospital Total Margin 2012	5.46% (-58%, 47%, 10.8%)	3.1% (-1184%, 70.8%, 26.3)	5.46% (-58%, 47%, 10.8%)	3.2% (-1184%, 55.9%, 28.4)

Table 5 shows that the exclusions of hospitals with bed size greater than 717 beds makes the Section 1109 hospitals and comparison hospitals more comparable in terms of the hospital characteristics. The additional exclusion of hospitals located in States without Section 1109 hospitals also makes the study population and comparison population more comparable in terms of hospital characteristics. Based on this analysis, the hypotheses in this study will be evaluated using a data set that excludes hospitals with a bed size greater than 717 beds and excludes hospitals in States without section 1109 hospitals.

Table 6 shows the average performance (as well as the standard deviation, minimum and maximum) for 30-day readmissions and mortality rates for heart failure, AMI and pneumonia for Section 1109 hospitals and the comparison hospitals, based on a performance period from July 1, 2008 to June 30, 2011, before Section 1109 hospitals received funding under Section 1109. It also shows the average performance (as well as the standard deviation, minimum and maximum) for 30-day readmission rates and 30- day mortality rates for heart failure, AMI and pneumonia for Section 1109 hospitals and the all other IPPS hospitals, based on a performance period from July 1, 2012 to June 30, 2015, which covers the period after the Section 1109 hospitals received money under that provision. On average, Section 1109 hospitals have lower readmission rates on the three conditions compared to the comparison hospitals. The readmission rates declined both for the Section 1109 hospitals and comparison hospitals over time. The Section 1109 hospitals have higher mortality rates than comparison hospitals, both for the baseline period and post-intervention period, and the mortality rates decline both for the Section 1109 hospitals and comparison hospitals between the baseline period and post-intervention period.

Table 6: Descriptive Statistics on the Dependent Variables in the Study

	Overall		Section 1109 Hospitals		Comparison Hospitals	
Variable	**No. of Observations**	**Mean Std Dev Minimum Maximum**	**No. of Observations**	**Mean Std Dev Minimum Maximum**	**No. of Observations**	**Mean Std Dev Minimum Maximum**
Baseline AMI Mortality Rate	1951	15.487	288	15.642	1663	15.459
		1.486		1.403		1.498
		10.1		10.5		10.1
		21.9		20		21.9
Post Period AMI Mortality Rate	1784	14.075	260	14.226	1524	14.0488
		1.245		1.183		1.254
		9.4		11.2		9.4
		20		17.8		20
Baseline Heart Failure Mortality Rate	2417	11.637	359	12.338	2058	11.514
		1.59		1.482		1.582
		6.8		8.9		6.8
		18.1		18.1		17.5
Post Period Heart Failure Mortality Rate	2265	12.141	346	12.793	1919	12.023
		1.491		1.367		1.483
		7.1		9.7		7.1
		17.8		17.8		16.9
Baseline Pneumonia Mortality Rate	2444	12.037	364	12.414	2080	11.971
		1.833		1.674		1.852
		7.1		8.2		7.1
		19.3		17.6		19.3
Post Period Pneumonia Mortality Rate	2338	16.429	354	16.855	1984	16.354
		2.218		2.0387		2.241
		8.7		11.6		8.7
		26.8		23		26.8
Baseline AMI Readmission Rate	1739	19.101	247	18.366	1492	19.223
		1.673		1.767		1.625
		12.836		12.836		13.581
		26.039		23.158		26.039
Post Period AMI Readmission Rate	1626	16.529	236	16.031	1390	16.614
		1.0781		1.085		1.054
		11.667		11.667		12.488
		20.673		19.667		20.673
Baseline Heart Failure Readmission Rate	2471	24.506	36	23.474	2107	24.684
		1.942		1.761		1.917
		18.908		19.221		18.908
		33.263		28.969		33.263
Post Period Heart Failure Readmission Rate	2267	21.798	344	21.161	1923	21.912
		1.677		1.699		1.648
		16.209		16.209		16.513
		31.364		27.58		31.364
Baseline Pneumonia Readmission Rate	2483	18.462	369	17.846	2114	18.569
		1.469		1.318		1.469
		14.275		14.275		14.428
		24.184		23.195		24.184
Post Period Pneumonia Readmission Rate	2342	17.133	353	16.607	1989	17.226
		1.535		1.449		1.5314
		13.038		13.314		13.038
		24.746		21.474		24.746
Change in AMI Readmission Rate	1541	-2.559	218	-2.289	1323	-2.603
		1.688		1.7241		1.6782
		-9.179		-7.057		-9.179
		3.133		1.635		3.1329

Change in Heart Failure Readmission Rate	2253	-2.661 1.969 -10.108 3.503	344	-2.283 1.815 -7.463 2.127	1909	-2.729 1.988 -10.107 3.503
Change in Pneumonia Readmission Rate	2313	-1.314 1.626 -7.351 4.699	350	-1.23 1.534 -6.621 3.591	1963	-1.329 1.642 -7.351 4.699
Change in Heart Failure Mortality Rate	2237	0.491 1.679 -5.8 6.6	343	0.445 1.739 -4.6 5.8	1894	0.499 1.668 -5.8 6.6
Change in Pneumonia Mortality Rate	2300	4.4 2.197 -3.7 12.8	349	4.443 2.202 -3.7 11.1	1951	4.392 2.196 -3 12.8
Change in AMI Mortality Rate	1728	-1.368 1.597 -8.1 4.8	254	-1.351 1.569 -5.7 3.1	1474	-1.371 1.602 -8.1 4.8

The third hypothesis of this study focuses only on the Section 1109 hospitals, so Table 7 below shows summary statistics related to payment for only those hospitals. The table shows that the Section 1109 payment varied widely, so we also examine this variable as the logarithm of Section 1109 payments. We also consider standardizing the payments by calculating the Section 1109 payment per bed and calculation the logarithm of Section 1109 payment per bed.

Table 7: Summary Statistics for Section 1109 hospitals

Variable	Number of Observations	Mean	Standard Deviation	Median	Minimum	Maximum
Section 1109 Payment Amount	400	997,290	1,143,328	530,405	1358	6,667,429
Section 1109 Payment Per Bed	400	3,990	1,860	3,954	15.91	13,219
Log of Section 1109 Payment	400	13.15	1.31	13.18	7.21	15.71
Log of Section 1109 Payment Per Bed	400	0.198	0.25	0.13	0.02	2.37

The next table provides correlations of Section 1109 payments and covariates in the model. It shows that the payments are generally positively correlated with Medicare case mix, bed size, and discharges. Section 1109 payments are negatively correlated with rural status, for-profit ownership and government ownership.

Table 8: Pearson Correlations for Section 1109 payments and hospital covariates

Hospital Covariate	Section 1109 Payment	Section 1109 Payment Per Bed	Logarithm of Section 1109 Payment	Logarithm of Section 1109 Payment per Bed
Medicare Case Mix	0.5254*	0.5498*	0.5571*	-0.1359*
Total Margin	-0.0397	-0.0607	-0.0977	0.0909
Logarithm of Beds	0.7771*	0.3701*	0.8522*	-0.7797*
Logarithm of Medicare Discharges	0.7327*	0.6530*	0.9675*	-0.6499*
Rural	-0.4102*	-0.2409*	-0.3513*	0.1987*
Medicare Dependent Hospital	-0.1466*	-0.0610	-0.0871	0.0189
Sole Community Hospital	-0.1363*	-0.0213	-0.0516	-0.0389
For Profit Ownership	-0.1968*	-0.1316*	-0.2914*	0.3025*
Government Ownership	-0.0169	-0.1582*	-0.1334*	0.0011

*indicates statistically significant with p-value <0.05

The figures below show the distribution of the Section 1109 payments by hospital, the logarithm of Section 1109 payments by hospital and the logarithm of Section 1109 payments per bed by hospital. The distribution of the Section 1109 payments by hospital show that payments are skewed to higher values, which can bias the regression analyses. As a result, based on the distributions, we chose to use the logarithm of Section 1109 payments and logarithm of Section 1109 payments per bed, as the independent variable to evaluate the third hypothesis.

Figure 3: Distribution of Section 1109 Payments

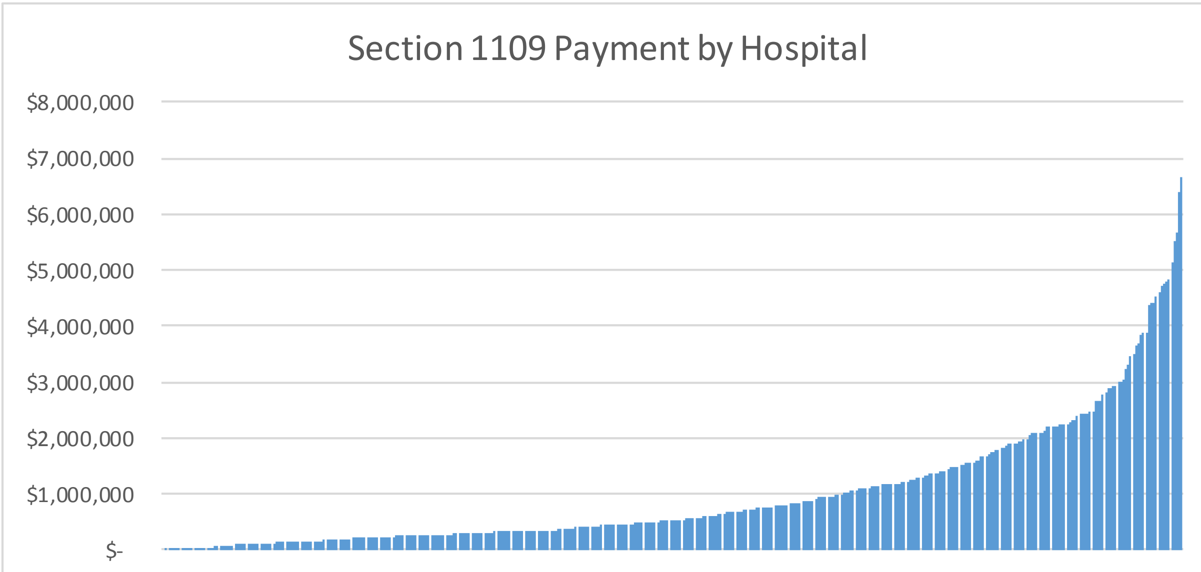


Figure 4: Distribution of the logarithm of Section 1109 Payments

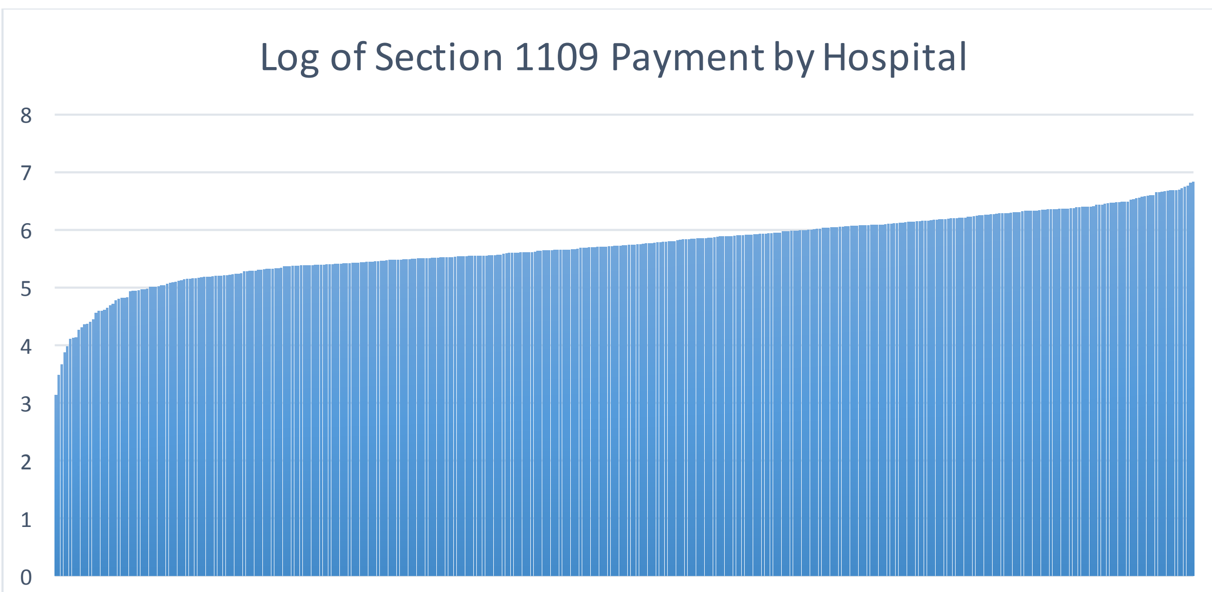
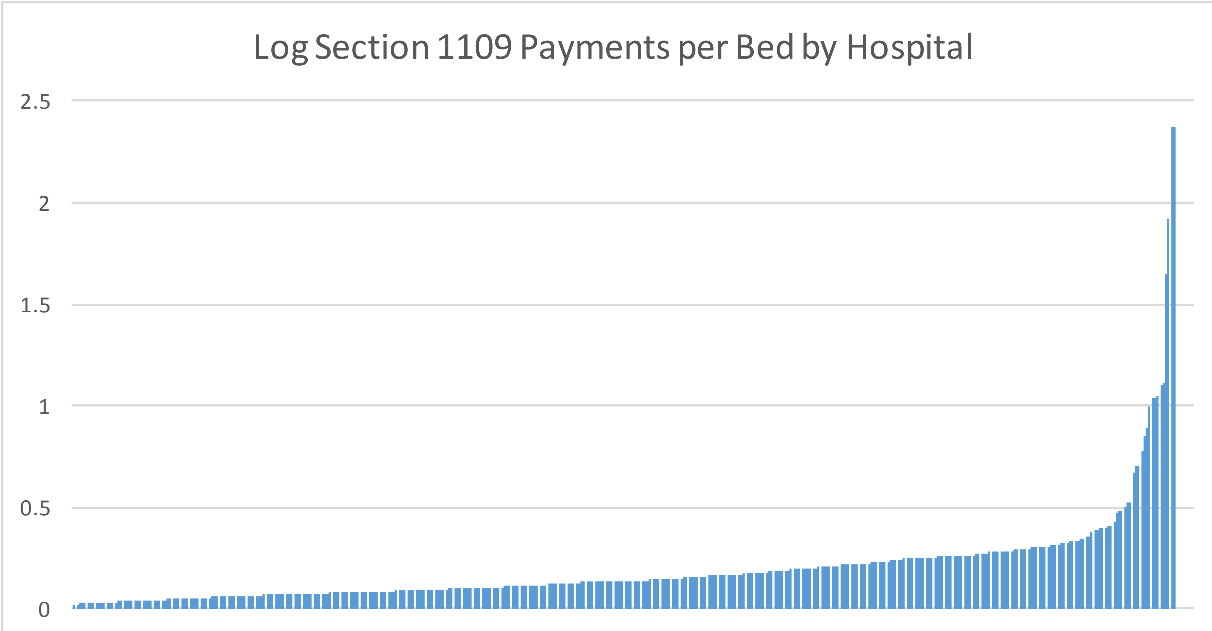


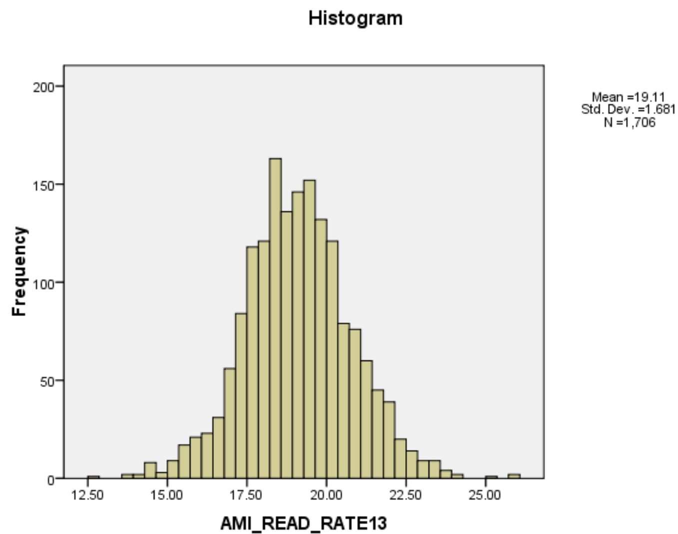
Figure 5: Distribution of the logarithm of Section 1109 Payments per bed



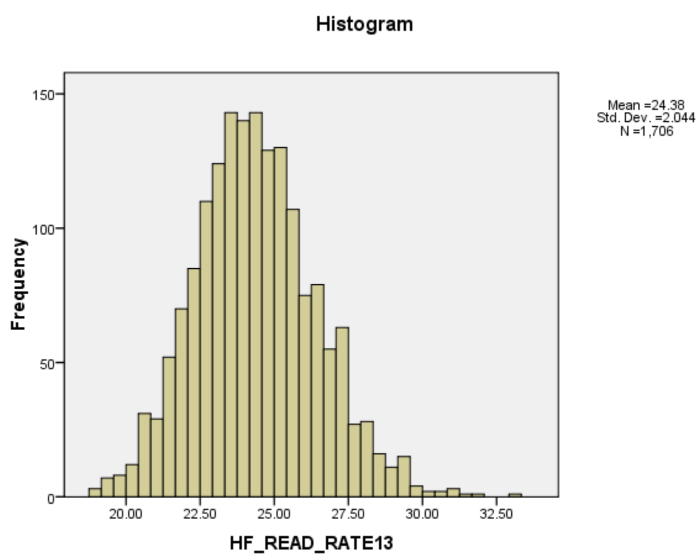
We also show the distributions of the dependent variables through histograms in the charts below. The purpose of the distributions is to identify if the variables are skewed which would inform whether the multivariate linear regression model is the appropriate model to use. The charts below show that the distributions are slightly skewed to the left or evenly distributed, which suggests that the multivariate linear regression model is the appropriate model to use, as later described below.

Figure 6: Distributions of the Quality of Care Indicators or Dependent Variables in Study

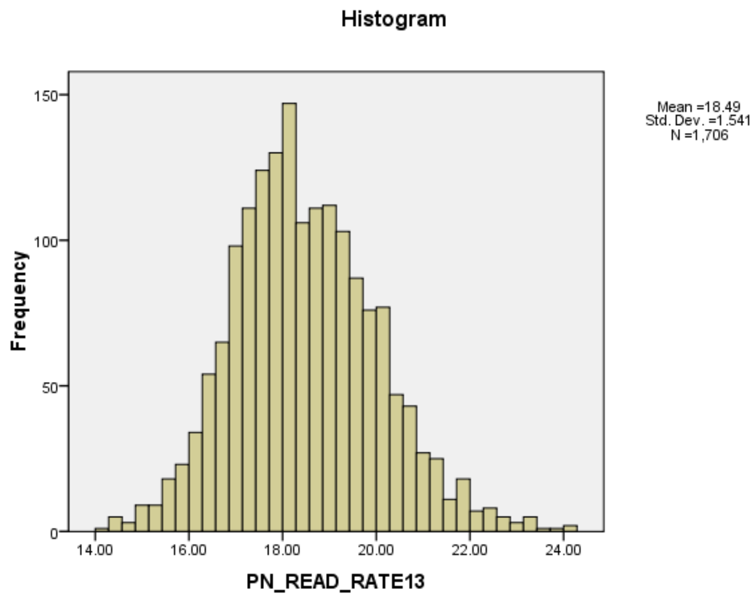
Distribution of Medicare FFS 30-Day AMI Readmission Rates Prior to Section 1109 Payments (2008-2011)



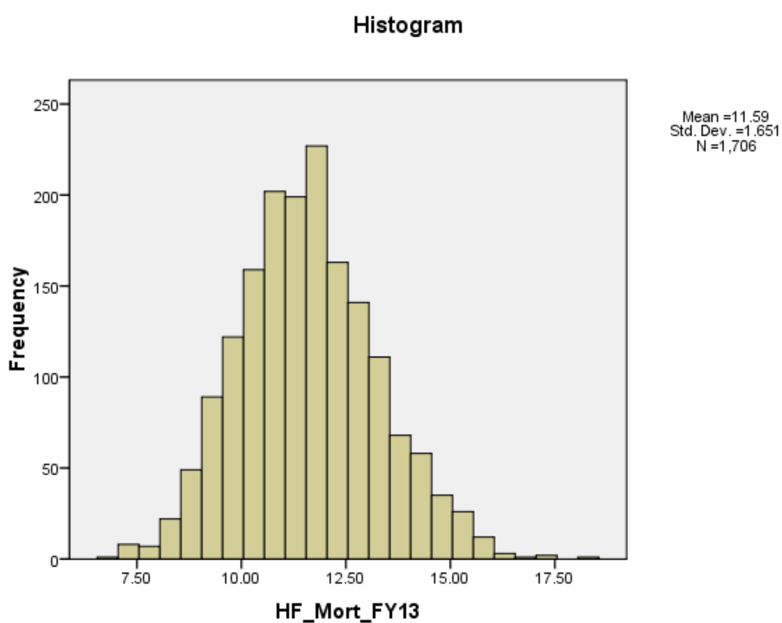
Distribution of Medicare FFS 30-Day Heart Failure Readmission Rates Prior to Section 1109 Payments (2008-2011)



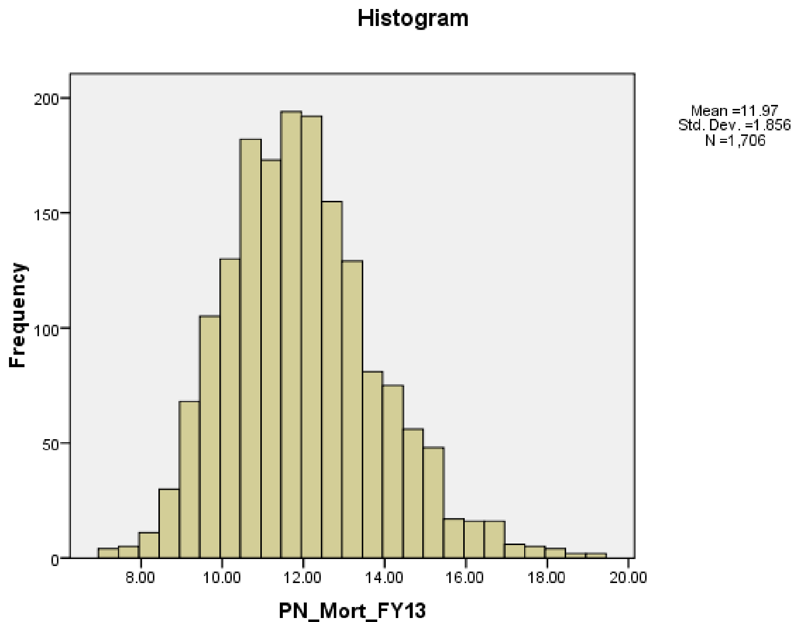
Distribution of Medicare FFS 30-Day Pneumonia Readmission Rates from Prior to Section 1109 Payments (2008-2011)



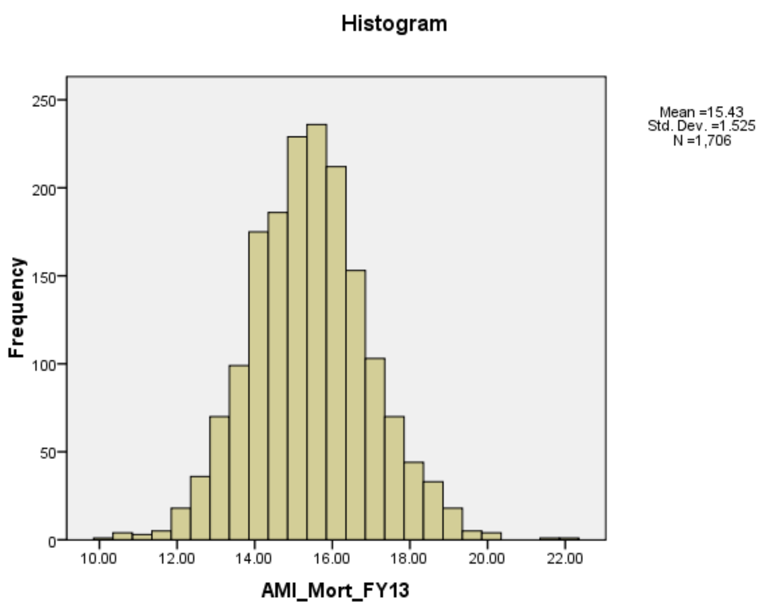
Distribution of Medicare FFS 30-Day Heart Failure Mortality Rates Prior to Section 1109 Payments (2008-2011)



Distribution of Medicare FFS 30 Day Pneumonia Mortality Rates Prior to Section 1109 Payments (2008-2011)



Distribution of Medicare FFS 30-Day AMI Mortality Rates Prior to Section 1109 Payments (2008-2011)



We also assess whether the dependent variables are correlated with each other for Section 1109 hospitals and the comparison hospitals as displayed below.

Table 9: Correlations of Quality of Care Indicators for Section 1109 hospitals versus Non-Section 1109 hospitals (beds <717, in states with Section 1109 hospitals)

Quality of Care Measure	Hospital Category	Baseline AMI Readmission Rate	Baseline Heart Failure Readmission Rate	Baseline Pneumonia Readmission Rate	Baseline AMI Mortality Rate	Baseline Heart Failure Mortality Rate	Baseline Pneumonia Mortality Rate
Baseline AMI Readmission Rate	Section 1109	1	0.414*	0.349*	0.188*	-0.079	-0.079*
	Non-Section 1109	1	0.395*	0.354*	0.026	-0.175*	-0.043
Baseline Heart Failure Readmission Rate	Section 1109	0.414*	1	0.358*	0.118*	-0.079	0.058
	Non-Section 1109	0.395*	1	0.459*	0.011	-0.118*	-0.050*
Baseline Pneumonia Readmission Rate	Section 1109	0.349*	0.358*	1	0.081	-0.099	0.018
	Non-Section 1109	0.354*	0.459*	1	-0.004	-0.155*	0.045*
Baseline AMI Mortality Rate	Section 1109	0.188*	0.118*	0.081	1	0.162*	0.176*
	Non-Section 1109	0.025	0.011	-0.004	1	0.284*	0.308*
Baseline Heart Failure Mortality Rate	Section 1109	-0.078	-0.079	-0.099	0.162*	1	0.371*
	Non-Section 1109	-0.175*	-0.118*	-0.155*	0.284*	1	0.388*
Baseline Pneumonia Mortality Rate	Section 1109	-0.078	0.058	0.018	0.176*	0.371*	1
	Non-Section 1109	-0.043	-0.050*	0.045*	0.308*	0.388*	1

*indicates statistically significant with p-value <0.05.

Quality of Care Measure	Hospital Category	Post period AMI Readmission Rate	Post period Heart Failure Readmission Rate	Post period Pneumonia Readmission Rate	Post period AMI Mortality Rate	Post period Heart Failure Mortality Rate	Post period Pneumonia Mortality Rate
Post period AMI Readmission Rate	Section 1109	1	0.407*	0.414*	0.176*	-0.116	0.100
	Non-Section 1109	1	0.412*	0.345*	0.059*	-0.129*	0.010
Post period Heart Failure Readmission Rate	Section 1109	0.407*	1	0.438*	0.098	-0.101	0.090
	Non-Section 1109	0.412*	1	0.461*	0.044	-0.088*	0.009
Post period Pneumonia Readmission Rate	Section 1109	0.414*	0.438*	1	0.135*	-0.033	0.022
	Non-Section 1109	0.345*	0.461*	1	0.002	-0.145*	0.048*
Post period AMI Mortality Rate	Section 1109	0.176*	0.098	0.135*	1	0.141	0.196
	Non-Section 1109	0.059*	0.044	0.002	1	0.282*	0.333*
Post period Heart Failure Mortality Rate	Section 1109	-0.116	-0.101	-0.033	0.141*	1	0.306*
	Non-Section 1109	-0.129*	-0.088*	-0.145*	0.282*	1	0.387*
Post period Pneumonia Mortality Rate	Section 1109	0.100	0.090	0.022	0.196*	0.306*	1
	Non-Section 1109	0.010	0.009	0.048*	0.333*	0.387*	1

*indicates statistically significant with p-value <0.05.

The readmission rates are generally correlated with each other for both Section 1109 hospitals and comparison hospitals, both during the baseline and post-performance period. The mortality rates are generally correlated with each other as well for both Section 1109 hospitals and comparison hospitals, both during the baseline and post-performance period.

The Appendix B, C and D provide additional descriptive analyses, including Pearson Correlations for the independent variables, covariates and dependent variables and scatterplots of the baseline performance for the quality indicators versus the post-intervention performance for the quality indicators.

Results for Hypothesis 1

As stated earlier, the first null hypothesis of this study is that hospitals that are located in areas with low Medicare per beneficiary spending provide quality of care equivalent to all other hospitals, in terms of mortality rates for AMI, heart failure and pneumonia and readmission rates for AMI, heart failure and pneumonia. To test this hypothesis, we use two methods. First, we conduct an independent t-test. Second, we conduct a multivariate linear regression with covariates including bed size, Medicare case mix, number of Medicare FFS discharges for the hospital, the number of Medicare FFS discharges for the specific condition related to the dependent variable (ie. AMI, heart failure or pneumonia), total hospital margin, dummy variable for ownership status (government hospital versus for-profit versus not-for-profit), dummy variable for state that hospital is located in, rural versus urban status, Medicare dependent hospital status and sole community hospital status. If the hospital does not have the minimum number of cases to calculate the quality of care indicator, according to the CMS measure specifications, then the hospital's observation is excluded from the analysis.

T-Test Analysis

In this section, we present the results of various statistical tests. We focus our analysis for three groups of hospitals. Our first group consists of all acute care hospitals in the U.S. Our second group consists of hospitals with less than 717 beds as the maximum number of beds for both acute care hospitals that did and did not receive a bonus payment under Section 1109. Our third group includes only hospitals with less than 717 beds from states that had Section 1109 hospitals. As noted earlier, the reason for excluding beds greater than 717 was that no Section 1109 hospitals had beds greater than 717 and we wanted to ensure that the hospitals with extremely large bed sizes did not influence the results.

We begin with analyses to determine whether there are differences in quality of care indicators among hospitals that did not receive and that received bonus payments under Section 1109. For this purpose, we did 2-independent sample t-tests. This test is based on the assumptions that the samples are independent and the population distributions follow the normal distribution. However, as two independent samples t-tests are robust for large samples, the normality requirement is not as important for our analysis. According to one study, t-tests should be used for large sample studies even with heavily skewed data (Fagerland, 2012). We choose the results of t-tests based on outcomes of the Leveine's test regarding whether variances are equal. We use the Cochran approximation when variances are not equal. The quality of care indicators include 30-day mortality rates and 30-day readmission rates for heart failure, pneumonia, and AMI.

In Table 10A, we present two-independent samples t-tests for all hospitals. For all quality of care indicators, the p-values are less than 0.05, which means that the differences in the means for the quality indicators between hospitals that received Section 1109 payments and the hospitals that did not receive payments are statistically significant at this level. The Section 1109 hospitals have statistically significant higher (or worse) mortality rates for heart-failure (mean difference=0.8791), pneumonia (mean difference= 0.464) and AMI (mean difference=0.237) than non-Section 1109 hospitals. The Section 1109 hospitals have statistically significant lower (or better) readmission rates for heart failure (mean difference=-1.30), pneumonia (mean difference =-0.794) and AMI (mean difference=-0.951) than non-Section 1109 hospitals.

In Table 10B, we repeated the independent t-test analysis for hospitals with beds less than 717. The results are similar to those for all hospitals in Table 10A. For all quality of care indicators, the p-value is less than 0.05. The 30-day mortality indicators for pneumonia (mean difference=0.447), heart failure (mean difference= 0.855) and AMI (mean difference= 0.206) are higher (or worse) for hospitals that did not receive Section 1109 payments as compared to hospitals that received payments. The 30 day readmission rates are lower (or better) for hospitals that did receive Section 1109 payment compared to hospitals that did not receive the Section 1109 payment. Again, the quality of care indicators are mixed between hospitals that received and did not receive Section 1109 payments.

In Table 10C, we examined the quality of care indicators of hospitals with beds less than 717 limited to states where there were hospitals that received the Section 1109 payments. The results are somewhat consistent with the two previous analyses. Our analysis indicates that hospitals that received Section 1109 payments have statistically significant higher 30-day heart failure (mean difference=0.824, p-value= 0) and pneumonia mortality rates (mean difference=0.443, p-value=0) than hospitals that did not receive payments. However, while the 30 day mortality rate for AMI is higher for Section 1109 hospitals than non-Section 1109 hospitals, the difference is not statistically significant (mean difference=0.1821, p-value=0.055). The 30-day readmission rates for heart failure, pneumonia, and AMI were lower (or better in terms of quality of care) among hospitals that received payments in comparison to those that did not receive payments.

In summary, the independent t-test analyses show that the Section 1109 hospitals have statistically significant higher mean 30-day mortality rates for pneumonia and heart failure than non-Section 1109 hospitals, before they received the bonus payment, and that the Section 1109 hospitals have lower means for 30 day readmission rates for heart failure, pneumonia and AMI than non-Section 1109 hospitals. Furthermore, the mean differences do not vary significantly when we trim the data set to exclude hospitals with more than 717 beds and eliminate hospitals in States where there are no Section 1109 hospitals, which supports making those exclusions to the data set in order to make the Section 1109 hospitals and comparison hospitals more comparable.

Table 10A Independent t-tests for differences in quality (all hospitals)

Quality of Care Measure	Section 1109 Hospital	N	Mean	Std. Deviation	Mean Difference	P-value (2-tailed)	Assumption about equality of variances
Heart Failure Mortality Rate Baseline*	Y	359	12.338	1.482	0.879	0.000	Equal
	N	2722	11.459	1.566			
Pneumonia Mortality Rate Baseline*	Y	364	12.414	1.674	0.464	0.000	Not equal
	N	2748	11.950	1.855			
AMI Mortality Rate Baseline*	Y	288	15.642	1.403	0.237	0.0113	Equal
	N	2253	15.405	1.505			
Heart Failure Readmission Rate Baseline*	Y	364	23.474	1.761	-1.309	0.000	Not Equal
	N	2702	24.783	1.924			
Pneumonia Readmission Rate Baseline*	Y	369	17.846	1.317	-0.795	0.000	Not equal
	N	2710	18.641	1.512			
AMI Readmission Rate Baseline*	Y	247	18.366	1.767	-0.951	0.000	Equal
	N	1978	19.317	1.641			

*Indicates that the results are statistically significant

Table 10B Independent t-tests for differences in quality (hospitals with beds <717)

Quality of Care Measure	Section 1109 Hospital	N	Mean	Std. Deviation	Mean difference	P-value (2-tailed)	Assumption about equality of variances
Heart Failure Mortality Rate Baseline*	Y	359	12.338	1.483	0.855	0.000	Equal
	N	251	11.483	1.566			
Pneumonia Mortality Rate Baseline*	Y	364	12.414	1.674	0.447	0.000	Not Equal
	N	2677	11.967	1.857			
AMI Mortality Rate Baseline*	Y	288	15.642	1.403	0.206	0.027	Equal
	N	2182	15.436	1.495			
Heart Failure Readmission Rate Baseline*	Y	364	23.474	1.761	-1.296	0.000	Not Equal
	N	2633	24.770	1.915			
Pneumonia Readmission Rate Baseline*	Y	369	17.846	1.318	-0.780	0.000	Not Equal
	N	2761	18.626	1.496			
AMI Readmission Rate Baseline*	Y	247	18.3662	1.7673	-0.931	0.000	Equal
	N	1909	19.2971	1.6292			

*Indicates that the results are statistically significant

Table 10C Independent t-tests for differences in quality (hospitals with beds <717 from states that received payments)

Quality of Care Measure	Section 1109	N	Mean	Standard Deviation	Mean Difference	P-value (2-tailed)	Assumption about the equality of variances
Heart Failure Mortality Rate Baseline*	Y	359	12.338	1.483	0.8241	.000	Equal
	N	2058	11.514	1.582			
Pneumonia Mortality Rate Baseline*	Y	364	12.414	1.674	0.443	.000	Not Equal
	N	2080	11.971	1.852			
AMI Mortality Rate Baseline	Y	288	15.642	1.403	0.182	.055	Equal
	N	1663	15.460	1.498			
Heart Failure Readmission Rate Baseline*	Y	364	23.474	1.761	-1.21	.000	Not Equal
	N	2107	24.684	1.917			
Pneumonia Readmission Rate Baseline*	Y	369	17.846	1.318	-0.724	.000	Not Equal
	N	2114	18.57	1.469			
AMI Readmission Rate Baseline*	Y	247	18.366	1.767	-0.857	.000	Equal
	N	1492	19.222	1.625			

*Indicates that the results are statistically significant

Multivariate Linear Regression Analysis

The bivariate analyses described above and displayed in Tables 10A-10C consider the impact of one variable at a time. However, there are other hospital characteristics that can impact the quality of care indicators in this study. So we performed different multivariate regression analyses using the generalized linear model to account for the possible impact of those hospital characteristics on the quality of care indicators. The generalized linear model covers a wide range of linear models where a dependent variable may be linearly related to independent variables through a variety of link functions. We examined the distributions of the dependent variables, as shown earlier in Figure 3. The dependent variables can have several non-normal distributions. We modeled quality indicators as a gamma distribution. The Gamma distribution is appropriate when a variable consists of positive values and is skewed towards larger values. For the analysis, we used the following covariates in the analysis: Medicare hospital case mix, total hospital margin, Medicare Dependent Hospital status, Sole Community Hospital Status, ownership status, a dummy variable taking a value of 1 for rural hospitals, logarithm of hospital beds, logarithm of Medicare discharges and dummy variables for each state. We used a dummy variable representing 1 for hospitals that received payments and 0 otherwise as the independent variable.

The output parameters for both multivariate linear regression analyses are shown in Tables 11A-11G. The dummy variable for states was not found to be statistically significant for any of the quality of care indicators, so it is not reflected in the tables.

The analyses show that there is a statistically significant difference ($p < 0.05$) in mortality rates for AMI and heart failure between Section 1109 hospitals and comparison hospitals. Generally, the mortality rates are higher (or worse) for Section 1109 hospitals compared to comparison hospitals. According to Table 11A, the AMI mortality rates are 0.263 percentage points higher (or worse) for the Section 1109 hospitals than for the comparison hospitals. The heart failure mortality rate for Section 1109 hospitals is 0.725 percentage points higher (or worse) than for comparison hospitals (see Table 11B). These results are consistent with the results from the t-test analysis.

Tables 11D-F show the multivariate linear regression results for the 30-day readmission rates. The analyses show that there are statistically significant differences ($p < 0.05$) for all the readmission rate indicators for the Section 1109 hospitals as compared to the comparison hospitals. According to Table 10D, the 30-day readmission rate for AMI is 0.547 percentage points lower (or better) for Section 1109 hospitals as compared to non-Section 1109 hospitals. The 30-day readmission rate for pneumonia is 0.599 percentage points lower (or better) for Section 1109 hospitals as compared to non-Section 1109 hospitals and the 30-day readmission rate for heart failure is 0.923 percentage points lower for Section 1109 hospitals as compared to the comparison hospitals. These results are also consistent with the results from the t-test analysis.

Not all of the covariates in the model are statistically significant. For all of the readmission measures, the case mix index and for-profit status contribute to the readmission rates. A higher case mix index contributes to lower baseline readmissions rates for heart failure (coefficient=-2.65), pneumonia (coefficient=1.49) and AMI (coefficient=-1.39). For profit ownership status contributes to higher baseline readmission rates for heart failure (coefficient=-0.688), pneumonia (coefficient=0.458) and AMI (coefficient=0.235). The number of discharges for the heart failure and AMI mortality rate indicators were also statistically significant for those models where the higher the number of discharges, there was slightly lower mortality rates. Total hospital margin and rural status were not found to be statistically significant in their contribution to any of the dependent variables in the model.

Based on these analyses, we can reject the null hypothesis that the hospitals that are located in areas with the lowest quartile of Medicare per beneficiary spending and received bonus payments under Section 1109 have quality of care equivalent to comparison hospitals, specifically, in terms of 30-day mortality rates and, 30-day readmission rates (with the exception of the pneumonia mortality rate). More specifically, the hospitals that are located in areas with the lowest quartile of Medicare per beneficiary spending and received bonus payments under Section 1109 had worse performance on mortality rates and better performance on readmission rates. The F-statistic assesses the overall fit of the regression model, including all the covariates. The F-statistic for all the regression analyses are statistically significant ($p < 0.05$), which indicates that the model has a reasonable fit and supports the finding to reject the null hypothesis.

Table 11A Multiple Linear Regression Model with 30-Day AMI Mortality Rate as a dependent variable.

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	15.849	12.730	<.0001
Baseline AMI Discharges	-0.002	-5.670	<.0001
Medicare Case Mix	-0.845	-3.870	0.000
Total Margin	-0.002	-1.790	0.073
Logarithm of Bed Count	0.395	3.330	0.001
Logarithm of Medicare Discharges	-0.116	-0.900	0.367
Rural	0.262	2.120	0.035
Medicare Dependent Hospital Status	-0.002	-0.010	0.991
Sole Community Hospital Status	-0.088	-0.630	0.527
For Profit Ownership	0.238	2.320	0.021
Government Ownership	0.249	2.220	0.026
Section 1109 Hospital Status	0.263	2.130	0.033
Number of Observations	1691		
F-value	6.28		<.0001
R-squared	0.155		
R-squared(adj)	0.130		
Durbin-Watson	2.069		

Table 11B Multiple Linear Regression Model with 30-Day Heart Failure Mortality Rate as a dependent variable.

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	13.291	9.590	<.0001
Baseline Heart Failure Discharges	-0.001	-2.460	0.014
Medicare Case Mix	-0.304	-1.290	0.198
Total Margin	0.002	1.410	0.159
Logarithm of Bed Count	-0.226	-1.760	0.079
Logarithm of Medicare Discharges	0.165	1.080	0.281
Rural	0.119	0.880	0.376
Medicare Dependent Hospital Status	-0.056	-0.260	0.794
Sole Community Hospital Status	-0.009	-0.060	0.954
For Profit Ownership	-0.175	-1.570	0.117
Government Ownership	-0.048	-0.390	0.694
Section 1109 Hospital Status	0.725	5.420	<.0001
Number of Observations	1691		
F-value	6.050		<.0001
R-squared	0.150		
R-squared(adj)	0.125		
Durbin-Watson	2.022		

Table 11C Multiple Linear Regression Model with 30-Day Pneumonia Mortality Rate as a dependent variable

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	14.821	9.750	<.0001
Baseline pneumonia discharges	0.000	1.120	0.261
Medicare Case Mix	-0.581	-2.010	0.045
Total Margin	-0.002	-1.180	0.239
Logarithm of Bed Count	0.493	3.320	0.001
Logarithm of Medicare Discharges	-0.643	-3.730	0.000
Rural	0.216	1.390	0.164
Medicare Dependent Hospital Status	-0.147	-0.590	0.556
Sole Community Hospital Status	0.027	0.150	0.879
For Profit Ownership	0.286	2.220	0.027
Government Ownership	0.296	2.100	0.036
Section 1109 Hospital Status	0.289	1.870	0.062
Number of Observations	1691		
F-value	3.87		<.0001
R-squared	0.102		
R-squared(adj)	0.075		
Durbin-Watson	2.094		

Table 11D Multiple Linear Regression Model with 30-Day AMI Readmission Rate as a dependent variable

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	18.140	13.680	<.0001
Baseline AMI discharges	-0.001	-3.780	0.000
Medicare Case Mix	-1.386	-5.720	<.0001
Total Margin	-0.002	-1.410	0.158
Logarithm of Bed Count	0.364	2.850	0.004
Logarithm of Medicare Discharges	0.100	0.760	0.446
Rural	-0.189	-1.430	0.154
Medicare Dependent Hospital Status	0.164	0.770	0.443
Sole Community Hospital Status	-0.166	-1.110	0.266
For Profit Ownership	0.235	2.130	0.034
Government Ownership	0.170	1.410	0.158
Section 1109 Hospital Status	-0.547	-4.130	<.0001
Number of Observations	1691		
F-value	8.480		<.0001
R-squared	0.199		
R-squared(adj)	0.175		
Durbin-Watson	1.979		

Table 11E Multiple Linear Regression Model with 30-Day Pneumonia Readmission Rate as the dependent variable

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	15.835	13.420	<.0001
Baseline pneumonia discharges	-0.001	-2.490	0.013
Medicare Case Mix	-1.485	-6.680	<.0001
Total Margin	-0.002	-1.350	0.178
Logarithm of Bed Count	0.122	1.060	0.291
Logarithm of Medicare Discharges	0.512	3.830	0.000
Rural	-0.071	-0.590	0.554
Medicare Dependent Hospital Status	-0.115	-0.600	0.551
Sole Community Hospital Status	-0.152	-1.120	0.262
For Profit Ownership	0.458	4.560	<.0001
Government Ownership	0.259	2.370	0.018
Section 1109 Hospital Status	-0.599	-4.990	<.0001
Number of Observations	1691		
F-value	9.440		<.0001
R-squared	0.216		
R-squared(adj)	0.193		
Durbin-Watson	2.013		

Table 11F Multiple Linear Regression Model with 30-Day Heart Failure Readmission Rate as the dependent variable

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	24.473	15.050	<.0001
Baseline heart failure discharges	0.000	-1.410	0.160
Medicare Case Mix	-2.643	-9.630	<.0001
Total Margin	-0.001	-0.800	0.425
Logarithm of Bed Count	0.340	2.270	0.023
Logarithm of Medicare Discharges	0.211	1.190	0.235
Rural	0.176	1.120	0.261
Medicare Dependent Hospital Status	-0.350	-1.390	0.165
Sole Community Hospital Status	-0.496	-2.810	0.005
For Profit Ownership	0.688	5.280	<.0001
Government Ownership	0.299	2.100	0.036
Section 1109 Hospital Status	-0.923	-5.900	<.0001
Number of Observations	1691		
F-value	11.11		<.0001
R-squared	0.245		
R-squared(adj)	0.223		
Durbin-Watson	1.896		

Results for Hypothesis 2

The second null hypothesis of this study is that hospitals that received payments under Section 1109 had an equivalent change in quality of care in terms of a change in 30-day mortality rates and 30-day readmission rates, compared to hospitals that did not receive bonus payments under Section 1109. We compare changes in quality of care indicators before and after the Section 1109 payments. We calculate the differences by subtracting the rates of the quality of care indicators in the baseline period of July 1, 2008 to June 30, 2011 from the comparison period of July 1, 2012 through June 30, 2015. If the hospital does not have the minimum number of cases to calculate the quality of care indicator, according to the CMS measure specifications, then the hospital's observation is excluded from the analysis.

T-Test Analysis

We conducted the independent t-test analyses for hospitals with fewer than 717 beds and in states with hospitals that received Section 1109 money, and the results are presented in Table 12. A negative value for the mean value indicates that the readmission rate or mortality rate decreased, which means that quality of care improved. A positive value for the mean value indicates that the readmission rate or mortality rate increased or worsened over time.

The t-tests indicate that there are no statistically significant differences in the changes in the quality of care indicators for Section 1109 hospitals compared to non-Section 1109 hospitals other than changes in the 30-day readmission rates for heart failure and AMI. For the 30-day readmission rates for heart failure and AMI, the rates declined more for non-Section 1109 hospitals than for Section 1109 hospitals, which means that the readmission rates improved more for non-Section 1109 hospitals than for Section 1109 hospitals. The mean difference for the change in the AMI readmission rate is 0.315 (p-value=0.0108), which indicates that the non-Section 1109 hospitals on average had a greater reduction or greater improvement in their AMI readmission rate by 0.315 percentage points, as compared to the non-Section 1109 hospitals. Similarly, the mean difference for the change in the heart failure readmission rate is 0.446 (p-value=0), which indicates that the non-Section 1109 hospitals on average had a greater reduction or greater improvement in their heart failure readmission rate of 0.446 percentage points, as compared to the non-Section 1109 hospitals. For these two quality indicators, we would reject the null hypothesis that hospitals that received payments under Section 1109 had an equivalent change in quality of care as compared to non-Section 1109 hospitals. For the other quality of care indicators, we fail to reject the null hypothesis.

Table 12: Two-independent samples t-tests for changes in quality of care indicators before and after payment to Section 1109 hospitals (comparison hospitals with beds <717 and hospitals in states with Section 1109 hospitals)

Quality of Care Indicator	Section 1109 Hospitals	Number of Hospitals	Mean	Std. Deviation	Mean Difference	P-value (2-tailed)	Assumption about the equality of variances
Change in the 30 day AMI Readmission Rate*	Y	218	-2.289	1.724	0.315	0.0108	Equal
	N	1323	-2.604	1.678			
Change in 30 day Heart Failure Readmission Rate*	Y	344	-2.283	1.815	0.446	0.000	Not equal
	N	1909	-2.729	1.988			
Change in 30 day Pneumonia Readmission Rate	Y	350	-1.230	1.534	0.098	0.298	Equal
	N	1963	-1.329	1.642			
Change in 30 Day Heart Failure Mortality Rate	Y	343	0.445	1.739	-0.0539	0.585	Equal
	N	1894	0.499	0.924			
Change in 30 day Pneumonia Mortality Rate	Y	349	4.443	2.202	0.0504	0.693	Equal
	N	1951	4.393	2.197			
Change in 30 Day AMI Mortality Rate	Y	254	-1.351	1.570	0.0202	0.8525	Equal
	N	1474	-1.371	1.602			

*Indicates that the results are statistically significant with p-value < 0.05.

Multivariate Linear Regression Analysis

The bivariate analysis above considers the impact of one variable at a time. As we did in the first hypothesis, we performed a multivariate linear regression analyses using the generalized linear model. The generalized linear model covers a wide range of linear models where a dependent variable may be linearly related to independent variables through a variety of link functions. The dependent variable can have several non-normal distributions. We model quality indicators as a gamma distribution. The Gamma distribution is appropriate when a variable consists of positive values and is skewed towards larger values. According to the omnibus test, the model outperforms the intercept only model. For the multivariate regression analysis, we used the following covariates in the analysis: baseline performance on quality of care indicator of interest, baseline number of Medicare FFS discharges for the quality of care indicator of interest, Medicare case mix, total margin, Medicare dependent hospital status, sole community hospital status, ownership status, a dummy variable taking a value of 1 for rural hospitals and 0 otherwise, logarithm of hospital beds, logarithm of Medicare discharges and dummy variables for each state. We used a dummy variable representing 1 for hospitals that received payments and 0 otherwise as the independent variable. The results of these regression analyses are shown in Tables 13A-F below. The dummy variables for each state are not statistically significant, so they are not displayed in the tables.

The multivariate linear regression models show that the Section 1109 hospitals had statistically significant differences in the change in the performance of the quality of care indicators for certain conditions compared to the comparison hospitals. The coefficient in the regression represents the amount of the change in the quality of care indicator that the covariate contributes relative to the comparison group. In other words, a negative coefficient indicates that the quality of care indicator either improved more or worsened less, and a positive coefficient indicates that the quality of care indicator worsened more or improved less than the comparison group. The F-statistic assesses the overall fit of the regression model, including all the covariates. The F-statistics for all the regression analyses are statistically significant ($p < 0.05$), which indicates that the model has a reasonable fit and supports the finding to reject the null hypothesis. The change in the AMI readmission rate for Section 1109 hospitals is 0.256 percentage points lower (p-value = 0.005) as compared to the comparison hospitals. The change in the heart failure readmission rate for Section 1109 hospitals is 0.461 percentage points lower (p-value=0.001) as compared to non-Section 1109 hospitals. Similarly, the change in the pneumonia readmission rate for Section 1109 hospitals was 0.404 percentage points lower (p-value =0.002) as compared to non-Section 1109 hospitals. These results would indicate that the readmission rates improved more or worsened less for the Section 1109 hospitals compared to the comparison group. However, the change in the heart failure mortality rates was 0.401 percentage points higher (p-value=0.002) as compared to the comparison group, which indicates that these rates worsened or improved less for Section 1109 hospitals compared to the comparison group. For all the other quality of care indicators (change in mortality rates for pneumonia and AMI), the coefficient for the Section 1109 hospital status was not statistically significant. This indicates that we failed to reject the null hypothesis that hospitals that received payments under Section 1109 had an equivalent change in quality of care in terms of a change in 30-day mortality rates for AMI and pneumonia, compared to hospitals that did not receive bonus payments. We reject the null hypothesis that hospitals that received payments under Section 1109 had an equivalent change in quality of care in terms of a change in readmission rates for AMI, heart failure and pneumonia and mortality rates for heart failure.

Some of the covariates in the models are statistically significant. The baseline readmission rate and mortality rate covariates are statistically significant for all of the dependent variables. The coefficients for the baseline rates for readmissions and mortality are all negative, which indicates that the higher the rate results in improvement in the rate over time. The overall hospital Medicare case mix and for-profit ownership status are also statistically significant in the models where the change in the readmission rates are dependent variables. The hospital's Medicare case mix contributes to an improvement in the readmission rates over time (AMI coefficient=-0.392, heart failure coefficient=-1.01, pneumonia coefficient=-0.997). For-profit ownership status contributes to worsening readmission rates or less improvement over time (AMI coefficient= 0.195, heart failure coefficient=0.365, pneumonia coefficient=0.363). Medicare Dependent Hospital status and sole community hospital status did not influence the change in any of the quality of care indicators.

The F-statistic assesses the overall fit of the regression model, including all the covariates. The F-statistic for all the regression analyses are statistically significant ($p < 0.05$), which indicates that the model has a reasonable fit.

The statistically significant results of this analysis are consistent with the t-test results in both the regression analyses and t-test analysis was statistically significant for AMI and heart failure readmission rates. However, the results are directionally inconsistent in that the t-test results showed that the AMI and heart failure readmission rates for comparison hospitals improved more than for Section 1109 hospitals, but when the model is adjusted for hospital covariates, the results show that readmission rates improved more or worsened less for the Section 1109 hospitals than the comparison hospitals.

Table 13A Multiple Linear Regression Model with Change in 30-Day AMI Readmission Rate as a dependent variable.

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	11.441	11.940	<.0001
Baseline Readmission Rate for AMI	-0.849	-51.660	<.0001
Baseline discharges for AMI	-0.001	-4.710	<.0001
Medicare Case Mix	-0.392	-2.290	0.022
Total Margin	-0.001	-0.830	0.404
Logarithm of Bed Count	0.198	2.210	0.027
Logarithm of Medicare Discharges	0.183	1.910	0.056
Rural	-0.010	-0.100	0.919
Medicare Dependent Hospital Status	0.129	0.770	0.443
Sole Community Hospital Status	0.086	0.820	0.415
For Profit Ownership	0.195	2.550	0.011
Government Ownership	0.103	1.250	0.213
Section 1109 Hospital Status	-0.256	-2.790	0.005
Number of Observations	1506		
F-value	61.02		<.0001
R-squared	0.673		
R-squared(adj)	0.662		
Durbin-Watson	2.069		

Table 13B Multiple Linear Regression Model with 30-Day Heart Failure Readmission Rate as a dependent variable.

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	15.804	10.160	<.0001
Baseline Heart Failure Readmission Rate	-0.711	-32.490	<.0001
Baseline discharges for Heart Failure	0.000	-0.960	0.336
Medicare Case Mix	-1.010	-3.900	0.000
Total Margin	0.000	-0.020	0.982
Logarithm of Bed Count	0.266	1.950	0.052
Logarithm of Medicare Discharges	-0.098	-0.580	0.564
Rural	-0.289	-2.030	0.043
Medicare Dependent Hospital Status	0.360	1.400	0.163
Sole Community Hospital Status	0.279	1.730	0.084
For Profit Ownership	0.365	3.090	0.002
Government Ownership	0.271	2.130	0.034
Section 1109 Hospital Status	-0.461	-3.270	0.001
Number of Observations	1506		
F-value	24.19		<.0001
R-squared	0.449		
R-squared(adj)	0.430		
Durbin-Watson	2.037		

Table 13C Multiple Linear Regression Model with the change in the 30-Day Pneumonia Readmissions Rate as a dependent variable

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	9.613	7.450	<.0001
Baseline Pneumonia Readmission Rate	-0.681	-26.800	<.0001
Baseline discharges for Pneumonia	-0.001	-3.460	0.001
Medicare Case Mix	-0.997	-4.080	<.0001
Total Margin	0.000	-0.170	0.866
Logarithm of Bed Count	0.254	2.060	0.039
Logarithm of Medicare Discharges	0.243	1.640	0.100
Rural	-0.012	-0.090	0.926
Medicare Dependent Hospital Status	0.216	0.930	0.352
Sole Community Hospital Status	0.050	0.340	0.733
For Profit Ownership	0.363	3.400	0.001
Government Ownership	0.009	0.080	0.936
Section 1109 Hospital Status	-0.404	-3.180	0.002
Number of Observations	1506		
F-value	16.71		<.0001
R-squared	0.360		
R-squared(adj)	0.338		
Durbin-Watson	2.019		

Table 13D Multiple Linear Regression Model with the Change in the 30-Day Heart Failure Mortality Rate as a dependent variable

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	9.778	7.320	<.0001
Baseline Heart Failure Mortality Rate	-0.658	-28.770	<.0001
Baseline discharges for Heart Failure	0.000	-0.550	0.581
Medicare Case Mix	0.290	1.270	0.205
Total Margin	0.000	0.330	0.743
Logarithm of Bed Count	-0.052	-0.430	0.671
Logarithm of Medicare Discharges	-0.044	-0.280	0.776
Rural	0.129	1.010	0.314
Medicare Dependent Hospital Status	0.192	0.830	0.407
Sole Community Hospital Status	0.166	1.150	0.251
For Profit Ownership	-0.067	-0.640	0.525
Government Ownership	0.037	0.320	0.746
Section 1109 Hospital Status	0.401	3.170	0.002
Number of Observations	1506		
F-value	18.13		<.0001
R-squared	0.379		
R-squared(adj)	0.358		
Durbin-Watson	2.101		

Table 13E Multiple Linear Regression Model with Change in 30-Day Pneumonia Mortality Rate as the dependent variable

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	14.013	7.740	<.0001
Baseline Pneumonia Mortality Rate	-0.514	-17.960	<.0001
Baseline Discharges for Pneumonia	0.000	0.490	0.626
Medicare Case Mix	-0.183	-0.530	0.600
Total Margin	0.001	0.590	0.552
Logarithm of Bed Count	-0.298	-1.680	0.094
Logarithm of Medicare Discharges	-0.004	-0.020	0.986
Rural	0.309	1.670	0.095
Medicare Dependent Hospital Status	-0.558	-1.670	0.094
Sole Community Hospital Status	-0.144	-0.690	0.492
For Profit Ownership	-0.087	-0.570	0.571
Government Ownership	0.076	0.460	0.646
Section 1109 Hospital Status	0.134	0.740	0.459
Number of Observations	-0.655		
F-value	7.87		<.0001
R-squared	0.209		
R-squared(adj)	0.183		
Durbin-Watson	2.135		

Table 13F Multiple Linear Regression Model with Change in 30-Day AMI Mortality Rate as the dependent variable

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	9.876	8.540	<.0001
Baseline AMI Mortality Rate	-0.758	-35.390	<.0001
Baseline discharges for AMI	-0.001	-2.660	0.008
Medicare Case Mix	-0.187	-0.940	0.346
Total Margin	0.001	0.960	0.336
Logarithm of Bed Count	0.264	2.460	0.014
Logarithm of Medicare Discharges	-0.116	-0.960	0.336
Rural	-0.114	-1.020	0.309
Medicare Dependent Hospital Status	0.557	2.770	0.006
Sole Community Hospital Status	0.075	0.590	0.554
For Profit Ownership	0.084	0.910	0.362
Government Ownership	0.025	0.260	0.799
Section 1109 Hospital Status	0.168	1.530	0.126
Number of Observations	1506		
F-value	28.26		<.0001
R-squared	0.488		
R-squared(adj)	0.470		
Durbin-Watson	2.043		

Difference-in-Differences Model

The difference-in-differences model was also used to test this hypothesis. In this case, the independent variable is whether or not the hospital received Section 1109 funding. The dependent variables are the change in 30-day readmission rates and 30-day mortality rates before and after the qualifying hospitals received the Section 1109 funding. However, this model also takes into account the effect of time and assumes that there are no significant changes between the Section 1109 hospitals and the comparison hospitals relative to each other prior to the Section 1109 payments. A dummy variable is created to identify Section 1109 hospitals and non-Section 1109 hospitals. A dummy variable for the time period (year) is also created to take into account the time period of before versus after the Section 1109 payments were made. The interaction term of the year and Section 1109 status is the difference-in-differences estimator, and its coefficient reflects the magnitude of the association between the Section 1109 hospitals and the quality of care indicators.

The difference-in-differences model is run for each quality of care indicator in this study. The model uses the following covariates: Medicare Case Mix, total hospital margin, Logarithm of Bed Count, Logarithm of Medicare Discharges, Rural, Medicare Dependent Hospital Status, Sole Community Hospital Status, ownership status (For Profit Status and Government Status in comparison to not-for-profit status) and rural (expressed as a dummy variable). The difference-in-differences variable is the variable of interest in the analysis and if statistically significant, demonstrates that the change in the quality of care indicator for the Section 1109 hospitals is different from the change in the quality of care indicators for the comparison hospitals. The results of this analysis are shown in Tables 14A-F below.

The results show that there is a statistically significant difference in the change in quality of care indicators among Section 1109 hospitals compared to the comparison group for the readmission rates for AMI and heart failure. For the AMI readmission rate, the difference-in-difference coefficient shows that the change in the readmission rate for Section 1109 hospitals was 0.304 percentage points higher as compared to the comparison hospitals (p-value= 0.019). For the change in the heart failure readmission rate, the difference-in-difference coefficient shows that the change in the readmission rate for the Section 1109 hospitals was higher by 0.470 percentage points as compared to the comparison hospitals (p-value=0.0). For the other quality of care indicators of interest, the difference-in-difference coefficients were not statistically significant with p-values greater than 0.05.

Some of the covariates in the models are statistically significant. The hospital Medicare case mix index, the log of the bed count, the log of Medicare discharges and ownership status (for-profit and government) contributed to the change in the AMI and heart failure readmission rates. Higher hospital Medicare case mix contributes to improvements in the heart failure and AMI readmission rates over time, where the coefficient for the AMI readmission is -0.93 and the coefficient for the heart failure readmission rate is 1.996. The log of Medicare discharges, for-profit ownership status and government ownership status reduce the change in the readmission rates for AMI and heart failure. The coefficient for the log of Medicare discharges for AMI readmission is 0.155 and for heart failure readmission rate is 0.150. The coefficient for for-profit ownership for AMI readmission rate is 0.224 and for heart failure readmission rate is 0.481 and the coefficient for government ownership for AMI readmission rate is 0.145 and for heart failure readmission rate is 0.248.

These findings indicate that we failed to reject the null hypothesis that hospitals that received payments under Section 1109 had an equivalent change in quality of care in terms of a change in mortality rates for AMI, pneumonia and heart failure and the change in readmission rate for pneumonia. We fail to reject the null hypothesis for all other quality of care indicators.

Table 14A Difference in Difference Model with Change in 30-Day AMI Mortality Rate as the dependent variable.

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	15.542	25.740	<.0001
Baseline Discharges for AMI	-0.002	-9.160	<.0001
Medicare Case Mix	-0.522	-4.080	<.0001
Total Margin	-0.001	-1.210	0.228
Logarithm of Bed Count	0.379	5.420	<.0001
Logarithm of Medicare Discharges	-0.111	-1.520	0.129
Rural	0.167	2.250	0.025
Medicare Dependent Hospital Status	0.133	1.140	0.256
Sole Community Hospital Status	-0.019	-0.230	0.815
For Profit Ownership	0.153	2.430	0.015
Government Ownership	0.151	2.220	0.026
Section 1109 Hospital Status	0.276	2.940	0.003
Difference-in-Difference	0.007	0.050	0.956
Year	-1.382	-29.680	<.0001
Number of Observations	3629		
F-value	32.18		<.0001
R-squared	0.307		
R-squared(adj)	0.298		
Durbin-Watson	1.731		

Table 14B Difference in Difference Model with Change in 30-Day Heart Failure Mortality Rate as the dependent variable.

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	12.027	26.380	<.0001
Baseline Discharges for Heart Failure	-0.001	-5.180	<.0001
Medicare Case Mix	-0.023	-0.190	0.849
Total Margin	0.001	1.510	0.132
Logarithm of Bed Count	-0.137	-2.060	0.039
Logarithm of Medicare Discharges	0.172	2.530	0.012
Rural	0.151	2.140	0.033
Medicare Dependent Hospital Status	0.116	1.130	0.258
Sole Community Hospital Status	0.127	1.630	0.103
For Profit Ownership	-0.190	-3.060	0.002
Government Ownership	-0.045	-0.700	0.483
Section 1109 Hospital Status	0.569	6.070	<.0001
Difference-in-Difference	-0.045	-0.370	0.709
Year	0.498	10.600	<.0001
Number of Observations	4581		
F-value	16.130		<.0001
R-squared	0.151		
R-squared(adj)	0.142		
Durbin-Watson	1.682		

Table 14C Difference in Difference Model with the Change in the 30-Day Pneumonia Mortality Rate as the dependent variable

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	12.851	22.420	<.0001
Baseline Discharges for Pneumonia	0.000	0.400	0.689
Medicare Case Mix	-0.428	-2.500	0.013
Total Margin	-0.001	-1.130	0.259
Logarithm of Bed Count	0.229	2.600	0.009
Logarithm of Medicare Discharges	-0.190	-2.180	0.030
Rural	0.377	4.030	<.0001
Medicare Dependent Hospital Status	-0.135	-1.000	0.319
Sole Community Hospital Status	-0.024	-0.230	0.821
For Profit Ownership	0.147	1.770	0.077
Government Ownership	0.220	2.570	0.010
Section 1109 Hospital Status	0.400	3.200	0.001
Difference-in-Difference	0.042	0.270	0.790
Year	4.402	66.580	<.0001
Number of Observations	4652		
F-value	126.00		<.0001
R-squared	0.578		
R-squared(adj)	0.573		
Durbin-Watson	1.695		

Table 14D Difference-in-Difference Model with the Change in the 30-Day AMI Readmission Rate as a dependent variable

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	17.478	23.710	<.0001
Baseline Discharges for AMI	-0.001	-6.690	<.0001
Medicare Case Mix	-0.930	-6.910	<.0001
Total Margin	-0.001	-1.840	0.065
Logarithm of Bed Count	0.286	3.890	0.000
Logarithm of Medicare Discharges	0.155	2.010	0.044
Rural	-0.123	-1.520	0.130
Medicare Dependent Hospital Status	0.155	1.120	0.262
Sole Community Hospital Status	-0.055	-0.590	0.552
For Profit Ownership	0.224	3.340	0.001
Government Ownership	0.145	1.980	0.048
Section 1109 Hospital Status	-0.587	-5.730	<.0001
Difference-in-Difference	0.304	2.360	0.019
Year	-2.614	-53.150	<.0001
Number of Observations	3301		
F-value	78.22		<.0001
R-squared	0.546		
R-squared(adj)	0.539		
Durbin-Watson	1.843		

Table 14E Difference-in-Difference Model with Change in 30-Day Pneumonia Readmission Rate as a dependent variable

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	16.660	41.730	<.0001
Baseline discharges for pneumonia	0.000	-3.450	0.001
Medicare Case Mix	-1.284	-10.600	<.0001
Total Margin	-0.001	-1.140	0.256
Logarithm of Bed Count	0.205	3.420	0.001
Logarithm of Medicare Discharges	0.257	4.280	<.0001
Rural	-0.087	-1.340	0.179
Medicare Dependent Hospital Status	-0.001	-0.010	0.991
Sole Community Hospital Status	-0.043	-0.600	0.551
For Profit Ownership	0.353	6.120	<.0001
Government Ownership	0.160	2.700	0.007
Section 1109 Hospital Status	-0.546	-6.290	<.0001
Difference-in-Difference	0.084	0.760	0.449
Year	-1.283	-27.850	<.0001
Number of Observations	4674		
F-value	44.25		<.0001
R-squared	0.324		
R-squared(adj)	0.316		
Durbin-Watson	1.743		

Table 14F Difference-in-Difference Model with Change in 30-Day Heart Failure Readmission Rate as a dependent variable

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	24.938	46.850	<.0001
Baseline discharges for heart failure	0.000	-2.260	0.024
Medicare Case Mix	-1.996	-14.460	<.0001
Total Margin	0.000	-0.240	0.813
Logarithm of Bed Count	0.242	3.340	0.001
Logarithm of Medicare Discharges	0.150	2.010	0.045
Rural	0.075	0.960	0.338
Medicare Dependent Hospital Status	-0.002	-0.020	0.986
Sole Community Hospital Status	-0.213	-2.460	0.014
For Profit Ownership	0.481	6.970	<.0001
Government Ownership	0.248	3.460	0.001
Section 1109 Hospital Status	-0.989	-9.480	<.0001
Difference-in-Difference	0.470	3.520	0.000
Year	-2.762	-52.670	<.0001
Number of Observations	4602		
F-value	88.83		<.0001
R-squared	0.494		
R-squared(adj)	0.488		
Durbin-Watson	1.738		

Propensity Score Matching Analyses

The study also utilizes propensity score matching to evaluate this hypothesis. The goal of propensity score matching is to reduce bias or the effects of confounding in observational studies by creating two populations that are similar across a number of covariates using a match on a propensity score. The propensity score represents the probability of assignment to treatment conditional on a set of observed baseline covariates. In other words, the covariates including log of beds, rural status, log number of discharges, sole community hospital status, Medicare dependent hospital status, case mix, total hospital margin and ownership (for-profit and government vs. not-for-profit) are the independent variables to determine the probability that a hospital is a recipient of Section 1109 payments. When the propensity match is performed, the balance between the two samples is evaluated. Balance checking serves multiple purposes- it may be used to compare matches from multiple iterations of the propensity score model or from different matching algorithms, and it provides information for any trade-offs between the closeness of the match and final sample size. When using propensity scores, the imbalances in the final matched sample should be kept in mind and possibly adjusted for when analyzing study outcomes. The literature shows that typically one or more controls are matched to each case on the propensity score as closely as possible while maintaining an adequate sample size.

There are several methods to use propensity scores in the analysis of observational data. We use the following three methods in our analysis:

1) Inverse Probability of Treatment Weighing Method: In this method, we compute weights for each hospital based on its propensity score and use it in further analysis.
2) Stratification Method: In this approach, we rank hospitals by their propensity scores and group hospitals into several groups based on propensity scores. We then estimate the treatment effect for each strata and combine the results of the individual strata to get the final treatment effect.
3) Matching: In the matching procedure, for each Section 1109 hospital, we find one or more matching comparison hospitals based on their propensity scores. We use the matched sample to do subsequent analyses to determine the treatment effect. The matching analysis used is the greedy matching SAS macro developed by Hamill (Hamill, 2015). We use a caliper or the difference between propensity scores of the Section 1109 hospitals (treatment) and matched comparison observations to be less than 0.1.

We use the Inverse Probability of Treatment Weighting Method to test for differences in the outcome variables based on the SAS macros given in Lanehart et al. (Lanehart, 2012). Under this methodology, observations are weighted by the inverse probability of receiving the treatment that they actually received. Section 1109 hospitals (or the treatment group) receive a weight equal to 1/propensity score and comparison hospitals receive a weight equal to 1/ (1-propensity score) (Harder et al., 2010). The weights are then used in a weighted least squares regression model along with other predictor covariates. The regression results are presented in Table 15 below.

The results of Table 15 show that the change in the AMI readmission rate for Section 1109 hospitals is lower by 0.495 percentage points (p-value < 0.05), as compared to the comparison group, identified through the propensity score. Furthermore, it shows that the change in the heart failure readmission rate for Section 1109 hospitals is lower by 0.4175 percentage points (p-value < 0.05), as compared to the comparison group, identified through the propensity score. Lastly, the change in the pneumonia readmission rate is 0.2696 lower for the Section 1109 hospitals as compared to the comparison hospitals. The change in the heart failure mortality rate is 0.4272 higher for Section 1109 hospitals as compared to comparison hospitals. Furthermore, the change in the pneumonia mortality rate is 0.2202 higher (or worse) for Section 1109 hospitals as compared to the comparison hospitals. In this case, we reject the null hypothesis that there is no difference in the change in the readmission rates for AMI, heart failure and pneumonia and in the mortality rates for heart failure and pneumonia. We fail to reject the null hypothesis that there is no difference in the change in the AMI mortality rate for Section 1109 hospitals compared to the comparison hospitals. We note that a disadvantage with this approach is that extreme propensity scores can result in very large weights that can bias the treatment effect estimates (Austin, 2011; Shadish & Steiner, 2010).

The second analysis utilizes the stratification method. The Section 1109 hospitals and non-Section 1109 hospitals are ranked by propensity score and grouped into quintiles. This essentially creates matched groups among Section 1109 hospitals and comparison hospitals for each quintile. Quintiles are chosen because they have been used in many propensity score studies and have been shown to remove 90% of the bias due to measured confounders (Thoemmes & Kim, 2010). After t-tests are conducted for each stratum, the weighted mean for the Section 1109 hospitals and the matched comparison hospitals are calculated. And then the t-test was conducted on the combined weighted values. Results based on t-tests using stratification are given below in Table 16 and show that the mean difference in the change in the AMI readmission rate, heart failure readmission rate, pneumonia readmission rate and heart failure mortality rates are statistically significant (p-value <0.05) for the Section 1109 hospitals as compared to the matched comparison group. Specifically the mean difference in the change in the AMI readmission rate is 0.3338 percentage points lower for Section 1109 hospitals as compared to the non-Section 1109 hospitals. The mean difference in the change in the heart failure readmission rate is 0.2508 percentage points lower for Section 1109 hospitals as compared to the non-Section 1109 hospitals. The mean difference in the change in the pneumonia readmission rate is 0.2137 for Section 1109 hospitals as compared to comparison hospitals. The mean difference in the change in the mortality rate is 0.3742 for Section 1109 hospitals as compared to the comparison hospitals. For the other quality of care indicators, we failed to reject the null hypothesis that there is no difference in the change in the quality of care for Section 1109 hospitals and non-Section 1109 hospitals after Section 1109 payments were made.

The last propensity score analysis utilizes matching Section 1109 hospitals with comparison hospitals with beds fewer than 717 located in states with Section 1109 hospitals. Table 17 shows the means and standard deviations of the hospital covariates for the 400 Section 1109 hospitals and 2362 non-Section 1109 hospitals prior to matching. There are statistically significant differences (p-value < 0.05) between the Section 1109 hospitals as compared to the non-Section 1109 hospitals on the following characteristics: bed count, number of Medicare FFS discharges, rural status, sole community hospital status and for-profit ownership. Specifically, Section 1109 hospitals had an average of 137 beds as compared to non-Section 1109 hospitals with an average of 170 beds and Section 1109 hospitals had an average of 2200 Medicare FFS discharges as compared to 2362 discharges for non-Section 1109 hospitals. Section 1109 hospitals had a greater frequency of rural hospitals (49% versus 27%) and sole community hospitals (30% versus 12%) and had a lower frequency of having for-profit status (16% versus 26%) as compared to non-Section 1109 hospitals. These differences before matching indicate that these covariates could bias the results of this study and that matching on these covariates could mitigate this concern.

Table 18 shows the means and standard deviations for the covariates for Section 1109 hospitals and the matched comparison hospitals. The table shows that the differences in the means between the Section 1109 hospitals and the matched comparison hospitals are not statistically significant (p-value > 0.05). This indicates that the Section 1109 hospitals and matched comparison hospitals are not significantly different on these characteristics, and this is an appropriate matched dataset to evaluate the null hypothesis that there is no difference in the change in quality of care indicators between the Section 1109 hospitals and comparison hospitals after the Section 1109 payments were made.

We also considered matching Section 1109 hospitals with comparison hospitals located in the same state, if inter-state differences contributed to differences in the quality of care indicators. Table 19 shows the differences in the comparison hospitals and Section 1109 hospitals when matched on the covariates described above as well as matched on state. The table shows that after the match, there are still statistically significant differences between the comparison group and Section 1109 hospitals. These differences indicate that the match on state does not remove other differences that can impact the dependent variables in the study. Furthermore, it was challenging to find a match between Section 1109 hospitals and comparison hospitals based on propensity scores within 0.1 of each other. As the table shows, out of the 400 Section 1109 hospitals, we are only able to match on 281 hospitals. As a result, we use the match shown in Table 18 that does not limit the match on state.

Table 20 shows the results of the t-test for the matched data set where the independent variable is Section 1109 hospital status and the dependent variables are the changes in the quality of care indicator after the Section 1109 payment was made as compared to before the Section 1109 payment. However, only the mean difference (0.3242) in the change in the heart failure readmission rate is statistically significant. This indicates that we fail to reject the null hypothesis and that there is no difference in the change in the quality of care for the Section 1109 hospitals compared to matched non-Section 1109 hospitals.

The first two propensity score analyses (the Inverse Probability of Treatment Weighting method and the stratification method) provide some consistent results. The inverse probability weighting method and the stratification method had statistically significant results for the change in the AMI, pneumonia and heart failure readmission rate and for the heart failure mortality rate. In other words, both methods showed that there were statistically significant changes in those quality of care indicators for the Section 1109 hospitals as compared to the comparison hospitals. The third propensity score matching analysis only showed that the difference in the change in the heart failure readmission rate is statistically significant for Section 1109 hospitals as compared to the matched comparison hospitals, and a similar result was found using the inverse probability weighting method and the stratification method.

There are several limitations to the propensity score matching technique. First, the matching was conducted on a 1:1 basis with one Section 1109 hospital matched to one non-Section 1109 hospital. While there are 400 Section 1109 hospitals, there are 2362 non-Section 1109 hospitals that could have been matched with the Section 1109 hospital, which indicates that we could have had multiple comparison groups and variations on the match that could have resulted in a different outcome. Second, the caliper was set to 0.1 which means that a comparison hospital would need to have a propensity score within 0.1 of the propensity score of the Section 1109 hospital to match. However, if the caliper had been set to a different level, it would have resulted in a different comparison group. These methodological changes could have resulted in a different matched data set and provided different results. Third, matching methods can use only observed characteristics to construct the comparison group, since unobserved characteristics cannot be taken into account. Thus, we assume that there are no unobserved differences in the Section 1109 hospitals and comparison groups that are also associated with the outcomes of interest. Lastly, a limitation of this technique is that a proper matched group should be matched on baseline characteristics, to ensure that those characteristics are not impacted by the policy intervention, and matched on characteristics that we believe could impact the dependent variables. While the study mitigates some of these limitations, it is possible that we could have had different results based on different assumptions.

Table 15: Results of linear regression using weighted propensity score

Quality variable	Intercept	Treatment=1/Control=0	t-value	F value	R-squared
Change in the AMI Readmission Rate	-2.525	-0.495	-5.50*	30.24*	0.0195
Change in the Heart Failure Readmission Rate	-2.620	-0.418	-4.99*	24.91*	0.0111
Change in the Pneumonia Readmission Rate	-1.277	-0.269	-3.98*	15.82*	0.0069
Change in Heart Failure Mortality Rate	0.425	0.427	6.03*	36.32*	0.0162
Change in Pneumonia Mortality Rate	4.369	0.220	2.41*	6.82*	0.0026
Change in AMI Mortality Rate	-1.394	0.141	1.85	3.41	0.002

*indicates results are statistically significant

Table 16: T-test analysis comparing Section 1109 hospitals and comparison hospitals identified by stratification of propensity scores

Quality of Care Indicator	Mean Difference of the Treatment and Comparison	t-value
Change in the AMI Readmission Rate	-0.334	-2.98*
Change in the Heart Failure Readmission Rate	-0.251	-2.30*
Change in the Pneumonia Readmission Rate	-0.214	-2.26*
Change in Heart Failure Mortality Rate	0.374	3.61*
Change in Pneumonia Mortality Rate	0.222	1.62
Change in AMI Mortality Rate	0.167	1.47

*indicates results are statistically significant

Table 17: Means and Standard Deviations for Section 1109 hospitals and Comparison Hospitals before Matching

Covariates	Section 1109 Hospitals			Comparison Hospitals		
	Number of Observations	Mean	Standard Deviation	Number	Mean	Standard Deviation
Medicare Case Mix Index	400	1.442	0.303	2362	1.455	0.334
Total Margin	388	6.306	11.289	2187	3.988	28.294
Beds*	400	137.16	124.121	2362	170.23	142.200
Number of Medicare Discharges*	400	2202.82	2203.33	2362	2732.60	2568.484
Rural*	400	0.49	0.50	2362	0.27	0.440
Medicare Dependent Hospital	400	0.07	0.255	2362	0.06	0.239
Sole Community Hospital *	400	0.30	0.460	2362	0.12	0.330
For Profit Ownership*	400	0.16	0.362	2348	0.26	0.441
Government Ownership	400	0.15	0.355	2348	0.17	0.379
Propensity Score	400	0.204	0.119	2187	0.140	0.086

*Differences in means statistically significant at the 0.05 level.

Table 18: Means and Standard Deviations for Section 1109 hospitals and Comparison hospitals (hospitals <717 beds in states with Section 1109 hospitals) before and after Matching

		Section 1109 Hospitals		Comparison Hospitals		Difference in Means after Matching (Section 1109 hospital-comparison)	Difference in Means Prior to Matching (Section 1109 hospital-comparison)
Covariate	Number of Observations	Mean	Standard Deviation	Mean	Standard Deviation		
Medicare Case Mix Index	400	1.442	0.303	1.454	0.348	-0.012	-0.014
Total Margin	388	6.307	11.289	6.875	62.019	-0.568	2.319
Beds	400	137.1600	124.121	147.555	130.458	-10.395	-33.07*
Number of Medicare Discharges	400	2202.820	2203.330	2555.000	2580.21	-352.18*	-529.78*
Rural	400	0.490	0.501	0.495	0.501	-0.005	-0.22*
Medicare Dependent Hospital	400	0.070	0.256	0.073	0.259	-0.003	0.010
Sole Community Hospital	400	0.303	0.459	0.313	0.464	-0.010	0.180*
For Profit Ownership	400	0.155	0.362	0.170	0.376	-0.015	-0.100*
Government Ownership	400	0.148	0.355	0.163	0.369	-0.015	-0.020

*Differences in means statistically significant at the 0.05 level.

Table 19: Means and Standard Deviations for Section 1109 hospitals and Comparison hospitals (hospitals <717 beds in states with Section 1109 hospitals) before and after Matching, where hospitals are matched if located within the same state

		Section 1109 Hospitals		Comparison Hospitals		Difference in Means after Matching (Section 1109 hospital-comparison)	Difference in Means Prior to Matching (Section 1109 hospital-comparison)
Covariate	**Number of Observations**	**Mean**	**Standard Deviation**	**Mean**	**Standard Deviation**		
Medicare Case Mix Index	281	1.4002	0.2768	1.4475	0.3012	-0.0473*	-0.0135
Total Margin	276	5.2794	10.2176	5.9632	10.0948	-0.9011	2.3186
Beds	281	135.3701	119.8873	157.6406	133.6192	-22.27*	-33.07*
Number of Medicare FFS Discharges	281	2306.5100	2313.86	2634.68	2338.87	-328.2	-529.78*
Rural	281	0.4769	0.5004	0.3950	0.4897	0.0819*	-0.22*
Medicare Dependent Hospital	281	0.0890	0.2852	0.0819	0.2746	0.0071	0.01
Sole Community Hospital	281	0.2562	0.4373	0.2135	0.4105	0.0427	0.18*
For Profit Hospital	281	0.1495	0.3572	0.1673	0.3739	-0.0178	-0.1*
Government Owned Hospital	281	0.1744	0.3801	0.1068	0.3094	0,0676*	-0.02

*Differences in means statistically significant at the 0.05 level.

Table 20: Means and Standard Deviation of (Treatment-Control) for the Matched Section 1109 hospitals and non-Section 1109 Hospitals using propensity scores

Quality Indicator	Number of Observations	Mean Treatment-Control	t-value
Change in the AMI Readmission Rate	129	0.141	0.65
Change in the Heart Failure Readmission Rate	293	0.324	2.02*
Change in the Pneumonia Readmission Rate	302	0.062	0.46
Change in Heart Failure Mortality Rate	289	-1.965	-1.42
Change in Pneumonia Mortality Rate	299	-0.1367	-0.81
Change in AMI Mortality Rate	165	0.281	1.65

*Differences in means statistically significant at the 0.05 level.

Additional Analyses

We also tested this second hypothesis on a subset of hospitals. We were interested to see if Section 1109 hospitals with certain hospital characteristics had an equivalent change compared to other hospitals with the same characteristics. Specifically, we tested within the sole community hospitals whether Section 1109 sole community hospitals had equivalent change in quality of care compared to other sole community hospitals. Sole community hospital status is a unique Medicare payment designation for hospitals that have less than 50 beds, are located 25-35 miles from other hospitals and are the primary service area for Medicare beneficiaries. However, the results for our t-test, multivariate regression analysis and difference-in-differences analyses limited to sole community hospitals led us to fail to reject the null hypothesis.

Results for Hypothesis 3

The third hypothesis focuses only on the hospitals that received the funding. The null hypothesis is that hospitals that received a higher proportion of Section 1109 funding are not different in terms of improvement of quality of care than hospitals that received less funding under Section 1109. To test this hypothesis, first, two different correlation analyses were performed. First, a Pearson correlation analysis was performed comparing the payment amounts and payments per bed to the quality of care indicators and the results are in Table 21A. The correlations measure the strength and direction of the linear relationship between the independent variables and dependent variables. The correlation coefficient can range from -1 to +1, with -1 indicating a perfect negative correlation, +1 indicating a perfect positive correlation, and 0 indicating no correlation at all. The correlation coefficient suggests the extent to which you can predict the value of one variable given a value of the other variable. The Pearson correlation assumes normal distribution. The Pearson correlation may not be the appropriate assessment if the data deviates from normality and if there are outliers in the data. To address this limitation, a Spearman correlation was also performed, as it overcomes these distribution and outlier assumptions and is not affected by deviations in normality, and it examines the monotonic relationship between the independent variables and dependent variables. As shown in Table 21B, the Spearman correlation is a moderately better indicator for our data.

As described earlier, the bivariate analysis, like the Pearson and Spearman correlations, is not reliable because it does not take into effect the impact of other variables on the dependent variable. To overcome this issue, multivariate linear regression analyses are performed to examine the relationship of the independent variable of the amount of Section 1109 money received and the change in the dependent variables, including the mortality measures and readmissions measures with covariates of logarithm of bed size, logarithm of the number of Medicare FFS discharges, baseline performance of the quality of care indicator of interest, number of Medicare FFS discharges for the quality of care indicator, total hospital margin, Medicare case mix, rural versus urban status, Medicare Dependent Hospital status, sole community hospital status, for profit status and government status. The independent variable of the amount of money received by the hospital is expressed either as the logarithm of the total amount of funding the hospital received or as the amount of money received per bed. The dependent variables are the change in the quality of care measures, comparing the time period before the Section 1109 hospitals received their funding to after the Section 1109 hospitals received their funding.

Lastly, a difference-in-differences model is used with covariates of logarithm of bed size, logarithm of the number of Medicare FFS discharges, baseline performance of the quality of care indicator of interest, number of Medicare FFS discharges for the quality of care indicator, hospital margin, Medicare case mix, rural versus urban status, Medicare Dependent Hospital status, sole community hospital status, for profit status and government status. If the hospital does not have the minimum number of cases to calculate the quality of care indicator, according to the CMS measure specifications, then the hospital's observation is excluded from the analysis.

Pearson and Spearman Correlations

The Pearson correlations show that the amount of the Section 1109 payment is positively correlated with the change in the AMI readmission rate. The correlation coefficient is 0.139 with a p-value of 0.040, which signifies that it is statistically significant. However, a positive correlation indicates that the higher the payment, the greater the positive change in the readmission rate which indicates a worse quality of care. For all other quality of care indicators, there is no association in the amount of payment the Section 1109 hospitals received and the change in the quality of care.

The Spearman correlations show that the Section 1109 payment amount per bed is positively correlated with the change in the AMI readmission rate. The correlation coefficient is 0.142 with p-value of 0.036, which signifies that this result is statistically significant. Again, a positive correlation indicates that the higher the Section 1109 payment per bed size, the greater the positive change in the AMI readmission rate, which indicates worsening quality of care. For all other quality of care indicators, there is no association in the amount of payment the Section 1109 hospitals received and the change in the quality of care

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Table 21A: Pearson Correlations of Amount of Section 1109 Payments with the Quality of Care Indicators

Quality of Care Indicator (Dependent Variable)	Number of Observations	Amount of Section 1109 Payment		Logarithm of the Amount of Section 1109 Payment		Section 1109 Payment Per Bed Count		Logarithm of Section 1109 Payment Per Bed Count	
		Coefficient	P value	Coefficient	P value	Coefficient	P value	Coefficient	P value
Change in AMI Readmission Rate	218	0.139*	0.040	0.115	0.089	0.104	0.123	-0.046	0.503
Change in Heart Failure Readmission Rate	344	-0.004	0.933	-0.018	0.741	-0.009	0.853	0.045	0.405
Change in Pneumonia Readmission Rate	350	-0.023	0.666	-0.010	0.854	-0.073	0.168	-0.019	0.721
Change in Heart Failure Mortality Rate	343	-0.035	0.509	-0.005	0.927	-0.020	0.709	-0.023	0.670
Change in Pneumonia Mortality Rate	349	-0.034	0.518	-0.011	0.837	0.098	0.066	0.073	0.173
Change in AMI Mortality Rate	254	0.110	0.079	0.105	0.094	0.097	0.121	-0.055	0.387

* Coefficient is statistically significant at the 0.05 level.

Table 21B: Spearman Correlations of Amount of Section 1109 Payments with the Quality of Care Indicators

Quality of Care Indicator (Dependent Variable)	Number of Observations	Amount of Section 1109 Payment		Logarithm of the Amount of Section 1109 Payment		Section 1109 Payment Per Bed Count		Logarithm of Section 1109 Payment Per Bed Count	
		Coefficient	P value	Coefficient	P value	Coefficient	P value	Coefficient	P value
Change in AMI Readmission Rate	218	0.106	0.117	0.106	0.117	0.1419*	0.036	-0.066	0.331
Change in Heart Failure Readmission Rate	344	-0.019	0.720	-0.019	0.720	0.0003	0.996	0.030	0.581
Change in Pneumonia Readmission Rate	350	-0.032	0.549	-0.032	0.549	-0.093	0.084	0.003	0.961
Change in Heart Failure Mortality Rate	343	0.005	0.929	0.003	0.958	-0.020	0.711	-0.016	0.765
Change in Pneumonia Mortality Rate	349	-0.015	0.783	-0.016	0.764	0.088	0.101	0.087	0.107
Change in AMI Mortality Rate	254	0.111	0.076	0.111	0.077	0.090	0.151	-0.091	0.150

* Coefficient is statistically significant at the 0.05 level.

Multivariate Linear Regression Analysis

As stated earlier, the bivariate analyses such as the Pearson and Spearman correlations do not account for other factors such as hospital characteristics that can influence the dependent variables. Therefore, multivariate linear regression analyses were performed. The independent variable in the analysis is presented in two ways: 1) the logarithm of the Section 1109 payment and 2) the logarithm of Section 1109 payment per bed. Because Section 1109 payments were large and varied, as shown in the distributions in the descriptive statistics section, the independent variable was adjusted as the logarithm of the Section 1109 payment and the payment per bed. The dependent variables are the changes in the quality of care indicators, comparing the performance before and after the Section 1109 payments were made. The covariates in this study include logarithm of bed size, logarithm of the number of Medicare FFS discharges, total hospital margin, Medicare case mix, rural versus urban status, Medicare Dependent Hospital status, sole community hospital status, for profit status and government status. Multiple linear regression models were also run with Section 1109 payments and the logarithm of Section 1109 payments as the independent variable, and included in the Appendix. However, for the reasons described earlier, we do not believe that is the independent variable should be reflected as the Section 1109 payment amount or logarithm of Section 1109 payment because of their distributions. The results are in Tables 23A-F.

The regression analyses show that the change in the AMI readmission rate is statistically significant (coefficient= 8.51, p-value=0.047) which indicates that the higher the Section 1109 payment (expressed as a log of the Section 1109 payment per bed) contributes to an increase in the AMI readmission over time. The F-statistic assesses the overall fit of the regression model, including all the covariates. The F-statistic for all the regression analyses are statistically significant ($p < 0.05$), which indicates that the model has a reasonable fit.

Most of the covariates in each model are not statistically significant, except for the baseline quality of care indicators. The baseline quality of care indicator contributes to a more negative change, or improvement, in the quality of care indicator for Section 1109 hospitals. This suggests that the higher (or worse) the baseline readmission rate or mortality rate for Section 1109 hospitals, the more improvement the hospitals experienced over time.

We also note that while the Pearson and Spearman correlations showed that the amount of the Section 1109 payments is positively correlated with the change in the AMI readmission rate with a correlation coefficient of 0.139 with a p-value of 0.040, consistent with the findings from the multiple linear regression analysis. For all other quality of care indicators, we fail to reject the null hypothesis that the hospitals that received a higher proportion of Section 1109 funding are not different in terms of the level of change in quality of care than hospitals that received less funding under Section 1109.

Table 22A: Multivariate Regression Model with the Change in the AMI Readmission Rate as the dependent variable

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	8.434	2.67	0.008
Baseline Discharges for AMI	-0.001	-1.03	0.306
Baseline Readmission Rate for AMI	-0.809	-18.73	<.0001
Medicare Case Mix	-1.1480	-2	0.047
Total Margin	-0.002	-0.25	0.805
Logarithm of Bed Count	-0.210	-0.8	0.422
Logarithm of Medicare Discharges	-0.259	-0.59	0.553
Rural	-0.015	-0.07	0.942
Medicare Dependent Hospital Status	0.004	0.01	0.991
Sole Community Hospital Status	0.136	0.63	0.527
For Profit Ownership	0.767	3.07	0.002
Government Ownership	0.167	0.62	0.534
Logarithm of Section 1109 Payment	0.646	1.36	0.175
Number of Observations	216		
F-value	36.57		<.0001
R-squared	0.685		
R-squared(adj)	0.666		
Durbin-Watson	2.038		

Table 22B: Multivariate Regression Model with the Change in the Heart Failure Readmission Rate as the dependent variable

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	14.744	2.99	0.003
Baseline Discharges for Heart Failure	-0.0001	-0.13	0.897
Baseline Readmission Rate for Heart Failure	-0.552	-9.03	<.0001
Medicare Case Mix	-1.328	-1.48	0.142
Total Margin	-0.003	-0.29	0.775
Logarithm of Bed Count	0.666	1.63	0.107
Logarithm of Medicare Discharges	0.019	0.03	0.978
Rural	-0.182	-0.56	0.575
Medicare Dependent Hospital Status	1.415	2.61	0.009
Sole Community Hospital Status	0.086	0.26	0.798
For Profit Ownership	0.188	0.47	0.636
Government Ownership	0.453	1.08	0.281
Logarithm of Section 1109 Payment	-0.411	-0.57	0.571
Number of Observations	215		
F-value	8.74		<.0001
R-squared	0.342		
R-squared(adj)	0.303		
Durbin-Watson	2.073		

Table 22C: Multivariate Regression Model with the Change in the Pneumonia Readmission Rate as the dependent variable

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	14.388	3.43	0.0007
Baseline Discharges for Pneumonia	0.001	1.16	0.248
Baseline Readmission Rate for Pneumonia	-0.577	-8.13	<.0001
Medicare Case Mix	-0.981	-1.25	0.212
Total Margin	-0.006	-0.62	0.536
Logarithm of Bed Count	0.693	1.91	0.058
Logarithm of Medicare Discharges	-0.228	-0.36	0.721
Rural	-0.173	-0.6	0.549
Medicare Dependent Hospital Status	0.814	1.7	0.091
Sole Community Hospital Status	0.028	0.09	0.926
For Profit Ownership	-0.026	-0.07	0.942
Government Ownership	0.0322	0.09	0.932
Logarithm of Section 1109 Payment	-0.418	-0.65	0.518
Number of Observations	215		
F-value	8.74		<.0001
R-squared	0.286		
R-squared(adj)	0.244		
Durbin-Watson	1.721		

Table 22D: Multivariate Regression Model with the Change in the Heart Failure Mortality Rate as the dependent variable

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	7.212	1.76	0.079
Baseline Discharges for Heart Failure	-0.001	-1.8	0.073
Baseline Mortality Rate for Heart Failure	-0.771	-12.9	<.0001
Medicare Case Mix	-0.506	-0.69	0.491
Total Margin	0.002	0.17	0.868
Logarithm of Bed Count	-0.166	-0.48	0.632
Logarithm of Medicare Discharges	0.193	0.32	0.751
Rural	-0.069	-0.25	0.800
Medicare Dependent Hospital Status	-0.0015	0	0.997
Sole Community Hospital Status	-0.211	-0.75	0.453
For Profit Ownership	-0.317	-0.96	0.337
Government Ownership	-1.159	-3.27	0.001
Logarithm of Section 1109 Payment	0.255	0.42	0.678
Number of Observations	215		
F-value	16.27		<.0001
R-squared	0.491		
R-squared(adj)	0.461		
Durbin-Watson	2.111		

Table 22E: Multivariate Regression Model with the Change in the Pneumonia Mortality Rate as the dependent variable

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	7.7753	1.42	0.1562
Baseline Discharges for Pneumonia	-0.0001	-0.12	0.9082
Baseline Mortality Rate for Pneumonia	-0.6163	-7.93	<.0001
Case Mix	-0.1198	-0.12	0.9078
Total Margin	-0.0030	-0.23	0.8178
Logarithm of Bed Count	-1.1351	-2.34	0.0200
Logarithm of Medicare Discharges	0.0428	0.05	0.9596
Rural	-0.0377	-0.1	0.9216
Medicare Dependent Hospital Status	-0.2890	-0.45	0.6498
Sole Community Hospital Status	-0.0257	-0.07	0.9480
For Profit Ownership	0.5131	1.11	0.2675
Government Ownership	-0.3380	-0.67	0.5049
Logarithm of Section 1109 Payment	0.7122	0.83	0.4070
Number of Observations	215		
F-value	6.68		<.0001
R-squared	0.2842		
R-squared(adj)	0.2416		
Durbin-Watson	2.034		

Table 22F: Multivariate Regression Model with the Change in the AMI Mortality Rate as the dependent variable

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	3.5017	0.94	0.35
Baseline Discharges for AMI	-0.0018	-2.06	0.041
Baseline Mortality Rate for AMI	-0.789	-13.59	<.0001
Medicare Case Mix	-1.066	-1.72	0.086
Total Margin	-0.011	-1.33	0.184
Logarithm of Bed Count	-0.072	-0.23	0.815
Logarithm of Medicare Discharges	-0.095	-0.19	0.853
Rural	-0.128	-0.53	0.599
Medicare Dependent Hospital Status	0.718	1.78	0.077
Sole Community Hospital Status	0.139	0.55	0.580
For Profit Ownership	0.115	0.39	0.697
Government Ownership	-0.162	-0.51	0.607
Logarithm of Section 1109 Payment	0.754	1.37	0.172
Number of Observations	215		
F-value	17.63		<.0001
R-squared	0.512		
R-squared(adj)	0.483		
Durbin-Watson	1.889		

Table 23A: Multivariate Regression Model with the Change in the AMI Readmission Rate as the dependent variable

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	7.08	2.33	0.021
Baseline discharges for AMI	-0.001	-1.44	0.150
Baseline Readmission Rate for AMI	-0.799	-18.86	<.0001
Medicare Case Mix	-0.632	-1.42	0.158
Total Margin	-0.003	-0.35	0.728
Logarithm of Bed Count	0.654	1.49	0.137
Logarithm of Medicare Discharges	0.273	1.08	0.283
Rural	-0.064	-0.31	0.759
Medicare Dependent Hospital Status	-0.089	-0.26	0.798
Sole Community Hospital Status	0.201	0.94	0.346
For Profit Ownership	0.728	2.95	0.004
Government Ownership	0.131	0.49	0.623
Logarithm of Section 1109 Payment per bed	8.507	1.99	0.048
Number of Observations	215		
F-value	37.12		<.0001
R-squared	0.688		
R-squared(adj)	0.669		
Durbin-Watson	2.057		

Table 23B: Multivariate Regression Model with the Change in the Heart Failure Readmission Rate as the dependent variable

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	12.061	2.63	0.009
Baseline Discharges for Heart Failure	-0.0002	-0.19	0.848
Baseline Readmission Rate for Heart Failure	-0.555	-9.07	<.0001
Medicare Case Mix	-1.645	-2.27	0.024
Total Margin	-0.004	-0.31	0.755
Logarithm of Bed Count	0.640	0.96	0.339
Logarithm of Medicare Discharges	-0.287	-0.62	0.536
Rural	-0.173	-0.53	0.596
Medicare Dependent Hospital Status	1.368	2.48	0.014
Sole Community Hospital Status	0.070	0.21	0.833
For Profit Ownership	0.216	0.55	0.584
Government Ownership	0.400	0.95	0.341
Logarithm of Section 1109 Payment per bed	0.753	0.12	0.909
Number of Observations	215		
F-value	8.7		<.0001
R-squared	0.342		
R-squared(adj)	0.303		
Durbin-Watson	2.068		

Table 23C: Multivariate Regression Model with the Change in the Pneumonia Readmission Rate as the dependent variable

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	17.146	4.54	<.0001
Baseline Discharges for Pneumonia	0.001	1.46	0.145
Baseline Readmission Rate for Pneumonia	-0.579	-8.21	<.0001
Medicare Case Mix	-1.187	-1.87	0.063
Total Margin	-0.005	-0.54	0.589
Logarithm of Bed Count	-0.214	-0.36	0.718
Logarithm of Medicare Discharges	-0.581	-1.54	0.125
Rural	-0.125	-0.43	0.665
Medicare Dependent Hospital Status	0.966	1.99	0.048
Sole Community Hospital Status	-0.027	-0.09	0.929
For Profit Ownership	-0.0003	0	0.999
Government Ownership	0.102	0.27	0.785
Logarithm Section 1109 Payment per bed	-9.553	-1.67	0.096
Number of Observations	215		
F-value	7.02		<.0001
R-squared	0.294		
R-squared(adj)	0.252		
Durbin-Watson	1.738		

Table 23D: Multivariate Regression Model with the Change in the Heart Failure Mortality Rate as the dependent variable

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	14.2739	3.83	0.0002
Baseline Discharges for Heart Failure	-0.001	-1.26	0.210
Baseline Mortality Rate for Heart Failure	-0.769	-12.99	<.0001
Medicare Case Mix	-0.200	-0.34	0.731
Total Margin	0.003	0.32	0.746
Logarithm of Bed Count	-0.975	-1.73	0.085
Logarithm of Medicare Discharges	0.317	0.83	0.408
Rural	-0.032	-0.12	0.908
Medicare Dependent Hospital Status	0.198	0.43	0.667
Sole Community Hospital Status	-0.234	-0.84	0.401
For Profit Ownership	-0.336	-1.03	0.303
Government Ownership	-1.007	-2.86	0.005
Logarithm of Section 1109 Payment per bed	-10.179	-1.85	0.065
Number of Observations	215		
F-value	16.8		<.0001
R-squared	0.499		
R-squared(adj)	0.461		
Durbin-Watson	2.098		

Table 23E: Multivariate Regression Model with the Change in the Pneumonia Mortality Rate as the dependent variable

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	10.430	2.15	0.033
Baseline Discharges for Pneumonia	-0.0002	-0.17	0.866
Baseline Mortality Rate for Pneumonia	-0.614	-7.89	<.0001
Medicare Case Mix	0.363	0.43	0.666
Total Margin	-0.0032	-0.24	0.812
Logarithm of Bed Count	-0.779	-0.98	0.328
Logarithm of Medicare Discharges	0.612	1.23	0.222
Rural	-0.068	-0.18	0.859
Medicare Dependent Hospital Status	-0.279	-0.43	0.668
Sole Community Hospital Status	0.012	0.03	0.975
For Profit Ownership	0.471	1.02	0.307
Government Ownership	-0.293	-0.58	0.563
Logarithm of Section 1109 Payment per bed	2.377	0.31	0.756
Number of Observations	215		
F-value	6.61		<.0001
R-squared	0.282		
R-squared(adj)	0.239		
Durbin-Watson	2.042		

Table 23F: Multivariate Regression Model with the Change in the AMI Mortality Rate as the dependent variable

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	8.1504	2.3	0.022
Baseline Discharges for AMI	-0.002	-1.71	0.089
Baseline Mortality Rate for AMI	-0.781	-13.42	<.0001
Medicare Case Mix	-0.528	-1.1	0.274
Total Margin	-0.011	-1.28	0.202
Logarithm of Bed Count	0.034	0.07	0.948
Logarithm of Medicare Discharges	0.462	1.48	0.140
Rural	-0.151	-0.62	0.538
Medicare Dependent Hospital Status	0.782	1.89	0.059
Sole Community Hospital Status	0.168	0.67	0.504
For Profit Ownership	0.067	0.23	0.818
Government Ownership	-0.059	-0.19	0.852
Logarithm of Section 1109 Payment per bed	-0.613	-0.12	0.904
Number of Observations	215		
F-value	17.31		<.0001
R-squared	0.507		
R-squared(adj)	0.478		
Durbin-Watson	1.883		

Difference-in-Differences Model

Lastly, we evaluate this hypothesis using the difference-in-differences model. The dependent variables are the change in 30-day readmission rates and 30-day mortality rates. This model also takes into account the effect of time and assumes that there are no significant changes between the Section 1109 hospitals. A dummy variable for the time period (year) is created to take into account the difference in the time period of before versus after the Section 1109 payments were made. The Section 1109 variable is a dummy variable for Section 1109 hospital or not a Section 1109 hospital. The interaction term of the year and Section 1109 payment (expressed as the logarithm of Section 1109 payment per bed) is the difference-in-difference estimator, and its coefficient reflects the magnitude of the association between the Section 1109 payments and the quality of care indicators.

The difference-in-differences model is run for each quality of care indicator in this study. The analysis examines the following covariates: Medicare Case Mix, total hospital margin, Logarithm of Bed Count, Logarithm of Medicare Discharges, Rural, Medicare Dependent Hospital Status, Sole Community Hospital Status, ownership status (For Profit Status and Government Status in comparison to not-for-profit status) and rural (expressed as a dummy variable). The difference-in-difference variable is the variable of interest in the analysis and if statistically significant, demonstrates that the change in the quality of care indicator based on the payment amount (expressed as the logarithm of Section 1109 payments per beds). The results of this analysis are shown in Tables 24A-F below. We also conducted the difference-in-differences model using the independent variable expressed as the Section 1109 payments, logarithm of Section 1109 payments and Section 1109 payments per bed. The results of that analysis are included in the appendix.

The difference-in-differences model shows that there is a statistically significant difference change in quality of care in the heart failure mortality rate based on the Section 1109 payment (reflected as the logarithm of the Section 1109 payment per beds). It shows that Section 1109 payment (reflected as the log of Section 1109 payment per bed) contributes to a change in the heart failure mortality rate by -2.378 percentage points or that the heart failure mortality rate improved more for higher Section 1109 payments.

Some of the covariates in each of the models are statistically significant. Hospital Medicare case mix index influences the change in the quality of care indicators among Section 1109 hospitals such that higher case mix results in greater improvement in the quality of care indicator. The log of the bed count also influences the change in all of the quality of care indicators among Section 1109 hospitals such that higher bed counts show worsening or less improvement in the quality of care indicators with the exception of the heart failure mortality measure, where it has the opposite impact. For-profit ownership status influences all the quality of care indicators for the Section 1109 hospitals except in the change in the heart failure mortality rate. Section 1109 hospitals with a for-profit ownership status show worsening or less improvement in those quality of care indicators as compared to Section 1109 hospitals that are non-profit or government owned. Section 1109 hospitals that are rural experienced worsening or less improvement on the three mortality rates (coefficient for AMI=0.338, coefficient for heart failure=0.2204, coefficient for pneumonia=0.2834), as compared to the urban Section 1109 hospitals. Total hospital margin and Medicare Dependent Hospital status generally did not have a statistically significant association with the change in the quality of care indicators among the Section 1109 hospitals.

Table 24A Difference in Difference Model with Change in 30-Day AMI Mortality Rate as a dependent variable.

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	15.031	27.230	<.0001
Baseline Discharges for AMI	-0.002	-7.090	<.0001
Medicare Case Mix	-0.642	-3.940	<.0001
Total Margin	-0.002	-2.220	0.026
Logarithm of Bed Count	0.211	2.220	0.026
Logarithm of Medicare Discharges	0.064	0.650	0.518
Rural	0.334	3.460	0.0006
Medicare Dependent Hospital Status	-0.082	-0.540	0.591
Sole Community Hospital Status	-0.088	-0.830	0.408
For Profit Ownership	0.389	4.650	<.0001
Government Ownership	0.300	3.360	0.0008
Section 1109 Hospital Status	0.216	2.310	0.021
Difference-in-Difference	-2.160	-1.590	0.113
Year	-1.114	-5.660	<.0001
Number of Observations	2186		
F-value	30.60		<.0001
R-squared	0.155		
R-squared(adj)	0.149		
Durbin-Watson	1.882		

Table 24B Difference in Difference Model with Change in 30-Day Heart Failure Mortality Rate as a dependent variable.

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	10.5456	24.72	<.0001
Baseline Discharges for Heart Failure	-0.001	-5.39	<.0001
Medicare Case Mix	-0.131	-0.82	0.414
Total Margin	0.002	1.70	0.089
Logarithm of Bed Count	-0.264	-2.98	0.003
Logarithm of Medicare Discharges	0.359	4.01	<.0001
Rural	0.221	2.43	0.015
Medicare Dependent Hospital Status	0.096	0.72	0.474
Sole Community Hospital Status	0.024	0.24	0.809
For Profit Ownership	-0.138	-1.71	0.088
Government Ownership	0.031	0.37	0.715
Section 1109 Hospital Status	0.701	7.69	<.0001
Difference-in-Difference	-2.378	-2.39	0.017
Year	0.809	4.39	<.0001
Number of Observations	2186		
F-value	26.61		<.0001
R-squared	0.113		
R-squared(adj)	0.109		
Durbin-Watson	1.84		

Table 24C Difference in Difference Model with Change in 30-Day Pneumonia Mortality Rate as a dependent variable.

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	12.7598	28.51	<.0001
Baseline Discharges for Pneumonia	0.0001	0.44	0.658
Medicare Case Mix	-0.563	-2.71	0.007
Total Margin	-0.003	-1.91	0.057
Logarithm of Bed Count	0.229	2.19	0.029
Logarithm of Medicare Discharges	-0.174	-1.69	0.091
Rural	0.283	2.62	0.009
Medicare Dependent Hospital Status	-0.009	-0.06	0.951
Sole Community Hospital Status	-0.081	-0.69	0.491
For Profit Ownership	0.305	3.15	0.002
Government Ownership	0.418	4.20	<.0001
Section 1109 Hospital Status	0.449	4.13	<.0001
Difference-in-Difference	0.579	0.58	0.559
Year	4.353	21.16	<.0001
Number of Observations	2186		
F-value	169.07		<.0001
R-squared	0.447		
R-squared(adj)	0.444		
Durbin-Watson	1.877		

Table 24D Difference in Difference Model with Change in 30-Day AMI Readmission Rate as a dependent variable.

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	18.446	28.51	<.0001
Baseline Discharges for AMI	-0.001	0.44	0.658
Medicare Case Mix	-1.857	-2.71	0.007
Total Margin	-0.003	-1.91	0.057
Logarithm of Bed Count	0.429	2.19	0.029
Logarithm of Medicare Discharges	0.200	-1.69	0.091
Rural	-0.149	2.62	0.009
Medicare Dependent Hospital Status	0.176	-0.06	0.951
Sole Community Hospital Status	-0.218	-0.69	0.491
For Profit Ownership	0.205	3.15	0.002
Government Ownership	0.0837	4.20	<.0001
Section 1109 Hospital Status	-0.645	4.13	<.0001
Difference-in-Difference	3.082	0.58	0.559
Year	-2.645	21.16	<.0001
Number of Observations	1939		
F-value	81.74		<.0001
R-squared	0.3557		
R-squared(adj)	0.3513		
Durbin-Watson	1.811		

Table 24E Difference in Difference Model with Change in 30-Day Pneumonia Readmission Rate as a dependent variable.

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	17.1525	50.85	<.0001
Baseline Discharges for Pneumonia	-0.0008	-3.69	0.0002
Medicare Case Mix	-2.141	-13.94	<.0001
Total Margin	-0.003	-2.37	0.018
Logarithm of Bed Count	0.297	3.85	0.0001
Logarithm of Medicare Discharges	0.426	5.61	<.0001
Rural	-0.128	-1.57	0.116
Medicare Dependent Hospital Status	0.137	1.13	0.258
Sole Community Hospital Status	-0.131	-1.47	0.142
For Profit Ownership	0.213	2.91	0.004
Government Ownership	0.026	0.35	0.728
Section 1109 Hospital Status	-0.500	-6.10	<.0001
Difference-in-Difference	0.682	0.89	0.374
Year	-1.279	-8.11	<.0001
Number of Observations	2749		
F-value	67.43		<.0001
R-squared	0.243		
R-squared(adj)	0.239		
Durbin-Watson	1.749		

Table 24F Difference in Difference Model with Change in 30-Day Heart Failure Readmission Rate as a dependent variable.

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	25.1483	52.06	<.0001
Baseline Discharges for Heart Failure	-0.0003	-1.39	0.164
Medicare Case Mix	-3.0356	-16.47	<.0001
Total Margin	-0.002	-1.45	0.147
Logarithm of Bed Count	0.464	4.67	<.0001
Logarithm of Medicare Discharges	0.211	2.12	0.034
Rural	0.129	1.24	0.216
Medicare Dependent Hospital Status	0.109	0.71	0.479
Sole Community Hospital Status	-0.305	-2.67	0.008
For Profit Ownership	0.393	4.21	<.0001
Government Ownership	0.109	1.13	0.257
Section 1109 Hospital Status	-0.999	-9.47	<.0001
Difference-in-Difference	2.341	1.94	0.052
Year	-2.634	-12.10	<.0001
Number of Observations	2728		
F-value	119.03		<.0001
R-squared	0.363		
R-squared(adj)	0.360		
Durbin-Watson	1.737		

The chart below summarizes the findings by hypothesis and method to identify if there are consistent results across the various methodologies.

Table 25: Summary of Results

Quality of Care Indicator (Dependent Variable)	Null Hypothesis 1: Section 1109 hospitals quality of care that is equivalent to all other hospitals prior to receiving the Section 1109 payment		Null Hypothesis 2: hospitals that received payments under Section 1109 had an equivalent change in quality of care in terms of a change in 30-day mortality rates and readmission rates, compared to hospitals that did not receive bonus payments under Section 1109				Null Hypothesis 3: hospitals that received a higher proportion of Section 1109 funding are not different in terms of improvement of quality of care than hospitals that received less funding under Section 1109		
	T-test	**Multivariate Linear Regression**	**T-Test**	**Multivariate Linear Regression**	**Difference in Difference**	**Propensity Score**	**Pearson and Spearman Correlations**	**Multivariate Linear Regression**	**Difference in Difference**
Baseline AMI Readmission Rate (for hypothesis 1); Change in AMI Readmission Rate (for hypothesis 2, 3)	Mean difference= -0.9309; Section 1109 hospitals perform better than comparison .	Section 1109 coefficient= -0.547; Section 1109 hospitals perform better than comparison.	Mean difference=0.315; Section 1109 hospitals improved more than comparison.	Section 1109 coefficient= - 0.256; Change in AMI readmission rate is 0.256 lower or improved for Section 1109 hospitals than comparison.	DD coefficient=0.3 04; change in readmission rate for Section 1109 hospitals is 0.304 percentage points higher than comparison	The inverse probability weighting method and the stratification method had statistically significant difference for the change in the AMI readmission rate for Section 1109 hospitals compared to comparison.	Pearson correlation for Section 1109 payment=0.139; Spearman correlation for Section 1109 payment per bed size=0.141; The higher the Section 1109 funding, the higher (or worse) the readmission rate.	Log of Section 1109 payment per bed coefficient= 8.5073 which means that the higher the payment, the worse the change in the readmission rate	Fail to reject null hypothesis
Baseline Heart Failure Readmission Rate (hypothesis 1); Change in Heart Failure Readmission Rate (hypothesis 2, 3)	Mean difference= -1.296; Section 1109 hospitals perform better than comparison	Section 1109 coefficient= -0.923; Section 1109 hospitals perform better than comparison.	Mean difference=0.446; Section 1109 hospitals improved more than comparison.	Section 1109 coefficient= - 0.461; Change in the readmission rate is 0.461 lower or improved for Section 1109 hospitals than comparison.	DD coefficient=0.4 70; change in readmission rate for Section 1109 hospitals is 0.470 percentage points higher than comparison	The inverse probability weighting method, the stratification method and the propensity score matching had statistically significant difference for the change in the heart failure readmission rate for Section 1109 hospitals compared to comparison	Fail to reject null hypothesis	Fail to reject null hypothesis	Fail to reject null hypothesis

Table 25: Summary of Results									
Quality of Care Indicator (Dependent Variable)	**Null Hypothesis 1: Section 1109 hospitals quality of care that is equivalent to all other hospitals prior to receiving the Section 1109 payment**		**Null Hypothesis 2: hospitals that received payments under Section 1109 had an equivalent change in quality of care in terms of a change in 30-day mortality rates and readmission rates, compared to hospitals that did not receive bonus payments under Section 1109**				**Null Hypothesis 3: hospitals that received a higher proportion of Section 1109 funding are not different in terms of improvement of quality of care than hospitals that received less funding under Section 1109**		
	T-test	**Multivariate Linear Regression**	**T-Test**	**Multivariate Linear Regression**	**Difference in Difference**	**Propensity Score**	**Pearson and Spearman Correlations**	**Multivariate Linear Regression**	**Difference in Difference**
Baseline Pneumonia Readmission Rate (hypothesis 1); Change in Pneumonia Readmission Rate (hypothesis 2, 3)	Mean difference= -0.780; Section 1109 hospitals perform better than comparison	Section 1109 coefficient= -0.599; Section 1109 hospitals perform better than comparison.	Fail to reject null hypothesis	Section 1109 coefficient= -0.404; Change in readmission rate is 0.404 lower or improved for Section 1109 hospitals than comparison.	Fail to reject null hypothesis	The inverse probability weighting method and the stratification method had statistically significant difference for the change in the readmission rate for Section 1109 hospitals compared to comparison.	Fail to reject null hypothesis	Fail to reject null hypothesis	Fail to reject null hypothesis
Heart Failure Mortality Rate (hypothesis 1); Change in Heart Failure Mortality Rate (hypothesis 2, 3)	Mean difference= 0.855; Section 1109 hospitals perform worse than comparison	Section 1109 coefficient= 0.725; Section 1109 hospitals perform worse than comparison.	Fail to reject null hypothesis	Section 1109 coefficient=0.401; Change in mortality rate is 0.401 higher for Section 1109 hospitals than comparison.	Fail to reject null hypothesis	The inverse probability weighting method and the stratification method had statistically significant difference for the change in the mortality rate for Section 1109 hospitals compared to comparison.	Fail to reject null hypothesis	Fail to reject null hypothesis	Log of Section 1109 payment per bed coefficient=-2.37. The higher the log of the Section 1109 payment per bed, the more improvement over time.
Baseline Pneumonia Mortality Rate (hypothesis 1); Change	Mean difference= 0.477; Section 1109 hospitals	Fail to reject null hypothesis	Fail to reject null hypothesis	Fail to reject null hypothesis	Fail to reject null hypothesis	Fail to reject null hypothesis	Fail to reject null hypothesis	Fail to reject null hypothesis.	Fail to reject null hypothesis

Table 25: Summary of Results									
Quality of Care Indicator (Dependent Variable)	**Null Hypothesis 1: Section 1109 hospitals quality of care that is equivalent to all other hospitals prior to receiving the Section 1109 payment**		**Null Hypothesis 2: hospitals that received payments under Section 1109 had an equivalent change in quality of care in terms of a change in 30-day mortality rates and readmission rates, compared to hospitals that did not receive bonus payments under Section 1109**				**Null Hypothesis 3: hospitals that received a higher proportion of Section 1109 funding are not different in terms of improvement of quality of care than hospitals that received less funding under Section 1109**		
	T-test	**Multivariate Linear Regression**	**T-Test**	**Multivariate Linear Regression**	**Difference in Difference**	**Propensity Score**	**Pearson and Spearman Correlations**	**Multivariate Linear Regression**	**Difference in Difference**
in Pneumonia Mortality Rate (hypothesis 2, 3)	perform worse than comparison								
Baseline AMI Mortality Rate (hypothesis 1); Change in AMI Mortality Rate (hypothesis 2, 3)	Mean difference= 0.182; Section 1109 hospitals perform worse than comparison	Section 1109 coefficient= 0.263; Section 1109 hospitals perform worse than comparison	Fail to reject null hypothesis	Fail to reject null hypothesis	Fail to reject null hypothesis	Fail to reject null hypothesis	Fail to reject null hypothesis	Fail to reject null hypothesis	Fail to reject null hypothesis

Chapter 5: Discussion and Policy Implications

Key findings

The primary objective of this study is to determine whether the hospitals that benefitted from Section 1109 of the Affordable Care Act show any differences in the quality of care compared to hospitals that did not benefit from this provision. The study seeks to add to the literature of whether additional reimbursement is associated with better quality of care. The literature review showed inconsistent findings on the relationship between spending to medical providers and quality of care, Major study findings can be grouped in the following categories: 1) increased spending led to improved quality of care, 2) increased spending did not improve quality of care, 3) inconclusive of whether spending influenced quality of care.

Based on the Bazzoli framework and the literature review, this study examined whether increased reimbursement to hospitals, through the bonus payments provided under Section 1109 of the Affordable Care Act, impacts patient outcomes or quality of care. Furthermore, the framework considers how other factors influence the quality of care indicators including hospital characteristics, such as inpatient volume, bed size, ownership status, and the hospital's financial condition, measured by the hospital's total margin.

This study was evaluated through three hypotheses. The descriptive statistics showed the differences in the Section 1109 hospitals and comparison hospitals. The Section 1109 hospitals are located in the bottom quartile of counties for Medicare per capita spending and those hospitals tend to be more rural, have fewer discharges, have fewer beds and have a higher total hospital margin and tend to be more sole community hospitals as compared to non-Section 1109 hospitals (or acute care hospitals located in higher Medicare per capita spending counties). Section 1109 hospitals are comparable to the comparison hospitals with respect to the wage index, case mix and DSH patient percentage. This study contributes to the literature on what types of hospitals are low cost hospitals with respect to Medicare spending.

The first hypothesis examined whether the Section 1109 hospitals are equivalent to the non-Section 1109 hospitals with respect to certain quality of care indicators. The analyses resulted in a rejection of the null hypothesis which stated that prior to the intervention, the hospitals that are located in areas with the lowest quartile of Medicare per beneficiary spending and received bonus payments under Section 1109 had different performance than all other acute care hospitals, in terms of certain quality of care indicators, specifically, 30-day mortality rates and 30-day readmission rates. Section 1109 hospitals or hospitals that are located in low Medicare spending areas had lower Medicare FFS 30-day readmission rates and higher Medicare FFS 30-day mortality rates, which suggests that these hospitals had varied performance on quality of care indicators prior to receiving the funding under Section 1109. This finding is notable in that the condition-specific readmission rates are correlated with each other, and the condition-specific mortality rates are correlated with each other, but readmission rates and mortality rates are not consistently correlated with each other. Furthermore, not all of the covariates in the model, adapted from the Bazzoli framework, were statistically significant. The Medicare hospital case mix index and for-profit ownership status are associated with the readmission rates, where hospitals with a higher case mix had lower baseline readmission rates and for-profit hospitals had higher readmission rates. Total hospital margin and rural status were not found to be statistically significant in their association with any of the dependent variables in the model.

In summary, the analyses show that these Section 1109 hospitals located in the counties with the lowest Medicare per capita spending were different in that they had lower readmission rates and higher mortality rates than other acute care hospitals in the country.

The second hypothesis examined whether Section 1109 hospitals show any differences in changes in quality of care compared to other hospitals after they received the bonus money. To test this hypothesis, we conducted t-tests, multivariate linear regression models, difference-in-differences models and propensity score matching. The results are generally inconclusive where under certain statistical models, there were statistically significant differences in the change in quality of care between the Section 1109 hospitals and the comparison hospitals, and other statistical models did not show a statistically significant change in quality of care. More specifically, under each analysis, we failed to reject the null hypothesis that there was a statistically significant difference in the change in pneumonia mortality rate and the change in the AMI mortality rate for Section 1109 hospitals compared to the comparison hospitals. For the other quality of care indicators, the analyses showed statistically significant differences in the changes for Section 1109 hospitals compared to the comparison hospitals but the results were not directionally consistent across the statistical methods used.

Similar to the first hypothesis, not all of the covariates were statistically significant when evaluating the second hypothesis. The covariates were used in the multiple linear regression and difference-in-difference analyses. The baseline readmission rates and mortality rates were statistically significant in that the baseline measures did influence the extent of the change in the readmission rates and mortality rates over time. A hospital's case mix index continued to influence the change in the readmission rates where hospitals with a higher case mix had greater improvement in the readmission rates for heart failure, pneumonia and AMI. For-profit hospital ownership also influenced the change in the readmission and mortality rates where changes in those quality of care indicators worsened over time, as compared to government owned and non-profit hospitals.

Finally, the third hypothesis examined whether there are any differences in quality of care over time based on the amount of money Section 1109 hospitals received. It sought to answer whether the amount of money a hospital receives is related to the quality of care provided. The findings were also inconsistent and we generally failed to reject the null hypothesis. The Pearson and Spearman correlations and the multiple linear regression model found that the higher the Section 1109 payment, the worse the AMI readmission rate became over time. However, based on the difference-in-differences model, we fail to reject the null hypothesis that there is a difference in quality of care. In summary, there is no difference in the change in quality of care based on the amount of money received by the Section 1109 hospitals.

When examining the statistical significance of the covariates across the hypotheses and statistical models, not all of the covariates based on the conceptual framework were associated with the quality of care indicators. Generally, a hospital's case mix index appeared to influence the quality of care indicators where a higher case mix contributed to lower (or better) baseline readmission rates and mortality rates and greater improvement in the quality of care indicators over time. Hospitals with a higher case mix generally treat higher acuity or more complex patients, which may indicate a greater sophistication in treatment of care that can result in better outcomes. Second, ownership status influenced the quality of care indicators where hospitals that are for-profit had higher (or worse) baseline quality of care indicators and showed less improvement or worsening in quality of care over time as compared to hospitals that were non-profit or government owned. This could indicate that ownership structures of hospitals may influence hospital decision-making on quality of care. Baseline performance on quality of care influenced the change in quality of care over time where higher (or worse) baseline readmission rates and mortality rates led to greater improvement over time, as there was greater opportunity to improve. The other covariates in the models were not as influential. Hospital margin was generally not statistically significant, which suggests that this financial indicator does not influence quality of care. Special Medicare payment hospital designations such as Medicare Dependent Hospital status and Sole Community Hospital status, which are given to hospitals that treat a high proportion of Medicare beneficiaries or are the only hospital serving an area, did not influence quality of care. These findings suggest that there are fewer hospital characteristics than originally determined or there are other characteristics not captured in this study that influence quality of care or changes in quality of care over time.

Policy implications

This study can inform policymakers in several ways. First, the study provides some insight on the types of hospitals that are located in low Medicare spending areas. The descriptive statistics identify the types of hospitals that tend to be in counties with low Medicare spending and shows that hospitals in low spending areas tend to be rural, non-profit and have smaller number of beds and discharges. It also shows that low Medicare spending areas are distributed throughout the country and not limited to certain states or regions of the country. The results show that the hospitals located in low spending areas have lower readmission rates for AMI, heart failure and pneumonia and higher mortality rates for the same conditions compared to other hospitals, which indicates inconsistent quality of care. It can be of value to policymakers to show that hospitals in low spending areas may not provide high quality care. Furthermore, if the intent of the Section 1109 provision was to reward hospitals located in low spending areas, because it is a goal of the Medicare program to reduce costs, the findings show that the bonus money under Section 1109 rewarded hospitals that may not provide the best quality of care.

Second, the findings show that there is not a relationship between hospitals receiving additional reimbursement and improvement on quality of care. If policymakers are seeking to find ways to improve quality of care, simply providing additional funding may not achieve such a goal.

If policymakers were to use a similar mechanism of providing additional funds to low cost hospitals to incentivize quality of care, they could create stronger incentives or requirements to ensure that the funding is used towards quality improvement. Policymakers could structure the policy in the following ways: 1) technical assistance to hospitals in conjunction with additional funding; 2) require hospitals to report on how they spent the additional funding, 3) provide requirements to hospitals on how to use the funding, 4) tie additional funding to demonstration of quality improvement.

First, as described earlier, a significant proportion of Section 1109 hospitals are rural, small bed hospitals that generally have limited staffing, expertise and infrastructure. These types of hospitals would greatly benefit from additional technical assistance on how to use additional funds most effectively for quality improvement initiatives. Technical assistance could include sharing information on evidence-based interventions for quality improvement, conducting assessments for the hospitals on what areas need quality improvement, helping hospitals implement quality improvement interventions, and aggregating data and tools for hospitals to use to continuously monitor quality improvement. If policymakers wanted to incentivize low per capita spending hospitals to improve quality of care, providing technical assistance in conjunction with additional funding may help to achieve such a policy goal. Another approach that policymakers could use to incentivize hospital quality improvement would be to require hospitals to report on how they use additional funding and demonstrate that it was used towards quality improvement. Holding hospitals accountable by requiring them to report on how they use the additional funding could incentivize the hospitals to use that money towards quality improvement. Third, policymakers could be more prescriptive on how the low cost hospitals should use the additional funding, specifying that funding may only be used for certain activities directed towards quality improvement. If policymakers set the activities that the funding could be used towards, policymakers would be able to test the effectiveness of those quality improvement activities, and use those findings to inform future policies. Lastly, policymakers could tie funding to demonstrated quality improvement. Section 1109 distributed $400 million to hospitals through two allotments over two years. Policymakers could set a requirement to provide additional funding to these hospitals, but only provide the second allotment of funding if the hospital is able to demonstrate quality improvement on a specific set of measures that are a policy priority.

Study strengths and limitations

This study has several strengths and limitations. First, an advantage of this study design is that the data spans a long time frame, a six year timeframe, which allows us to measure quality of care prior to the Section 1109 hospitals receiving the bonus funding and after the Section 1109 hospitals received the bonus funding, without overlap in time frames. Second, the study includes the entire population of IPPS hospitals, and not a sample, which increases the validity and reliability of the study. A third strength of the study is that the dependent variables are objective measures. The study uses the CMS 30-day Medicare FFS condition specific readmission and mortality measures which are highly vetted, standardized measures that are used for public reporting and used for Medicare hospital quality payment programs. Furthermore, there is no testing effect in this analysis as the data used in the study are largely administrative data using claims information to calculate the readmission and mortality rate health outcomes. Fourth, the study utilizes a variety of statistical methods to evaluate each hypothesis, and the results are more reliable as several methodological approaches demonstrate consistent results. In summary, the strength of this study is the novelty of assessing whether a policy that provides for a one-time infusion of funding to low-cost hospitals contributes to improvements in quality of care using CMS quality of care indicators that span the duration of the policy.

The study also presents several limitations. First, the generalizability of the study is limited because the study identifies hospitals located in low spending areas based on Medicare spending and uses quality of care measures for the Medicare population. Because the data are limited to Medicare health outcomes, the results of the study could not be applied to the treatment for other populations, as the elderly population has unique health characteristics that may not be applied to other age groups. However, it is worth noting that the study can be generalizable in some respect because the study uses a national data set for acute care hospitals.

Second, while the study uses highly scrutinized quality measures and reflect quality of care for high cost and high volume conditions, the 30-day mortality and 30-day readmission rates measures have some limitations in that they do not represent the full spectrum of hospital care. As a result, the study may be limited in extrapolating the relationship between Medicare payment and quality of care.

Third, historical or maturation events could affect the internal validity of this study. Historical events or other Medicare payment policies could affect study results if an event disproportionately affects the control group versus the test group or vice versa, thus biasing the outcomes. It is also possible that regional events could impact the dependent variables in this study. Because the hospitals' quality of care measures are based on three years of claims data, a specific event during that time period could affect the results of that measure. For example, a natural disaster could affect a hospital's quality of care outcomes. In addition, an event could influence whether or not a hospital is included in the test group because a specific event could have resulted in a county having low Medicare spending allowing a hospital to qualify for a Section 1109 payment. However, the effect of maturation could be mitigated because the quality measures are based on three years of claims data. In addition, the issue of maturation can be mitigated by the sample size of this study with respect to both the test group and the control group.

Areas for Future Research

The study dataset presents opportunities for future research. First, we can further assess if there are any unique characteristics among hospitals that are located in areas with low Medicare per capita spending. This can provide insight on factors that contribute to low Medicare per capita spending. While the study showed that there are some differences in the Section 1109 hospitals and other hospitals, further research could be done in this area.

Second, the findings showed that there are generally no differences in changes in quality of care for Section 1109 hospitals compared to the comparison hospitals after the Section 1109 hospitals received additional funding, future research could examine if there are certain characteristics or types of Section 1109 hospitals where quality improvement was observed after Section 1109 hospitals received funding. Furthermore, future research could examine whether there are other measures of quality, not just quality limited to improvement in readmission rates and mortality rates, where Section 1109 hospitals improved after receiving the funding.

Lastly, research could be conducted to identify what types of hospitals do provide high quality care with respect to readmission rates and mortality rates including what hospital characteristics are associated with high and low quality. This research could help to inform if there are key criteria that are needed by hospitals in order to provide better quality of care.

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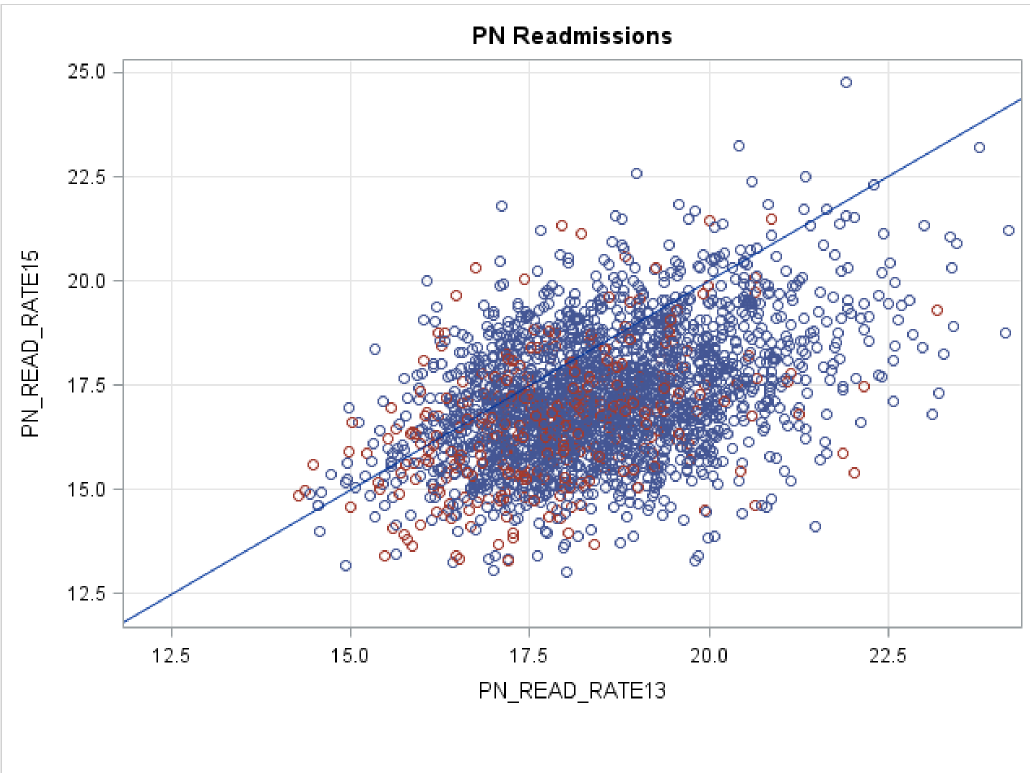
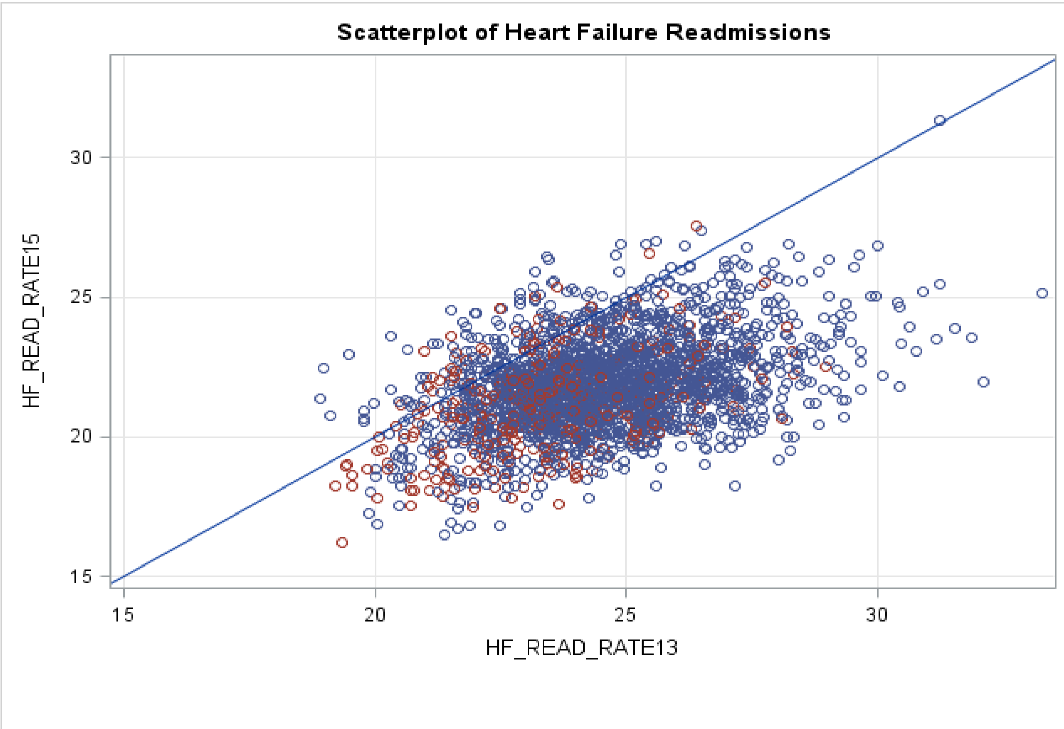
Appendices

Appendix A: Scatterplot of Baseline Dependent Variables Compared to Dependent Variables

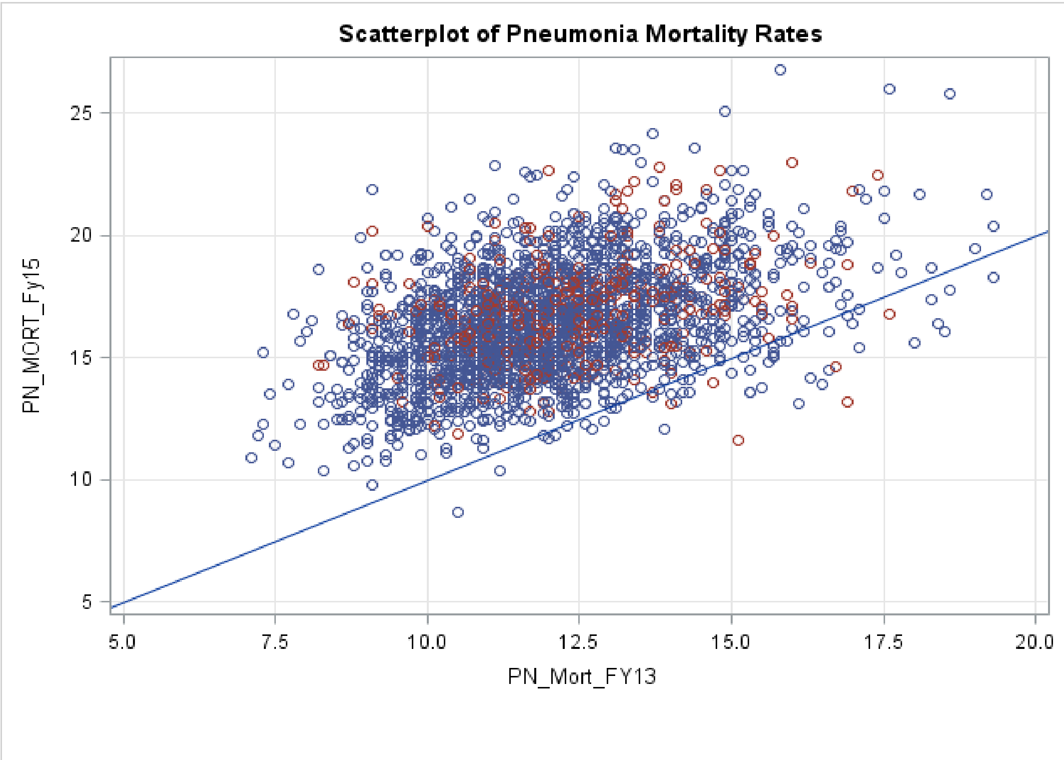
*The the Section 1109 hospitals, blue are the comparison hospitals

* the x-axis is the baseline performance on the quality of care indicator and the y-axis the post-period performance on the quality of care indicator

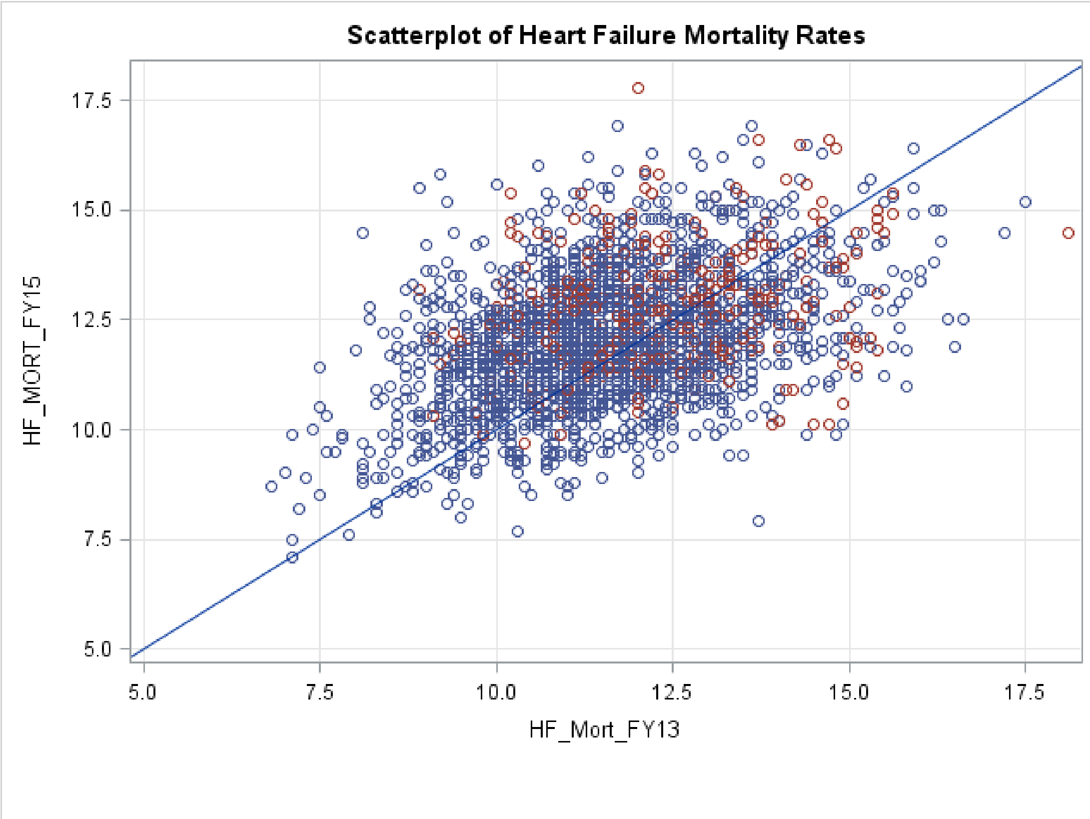


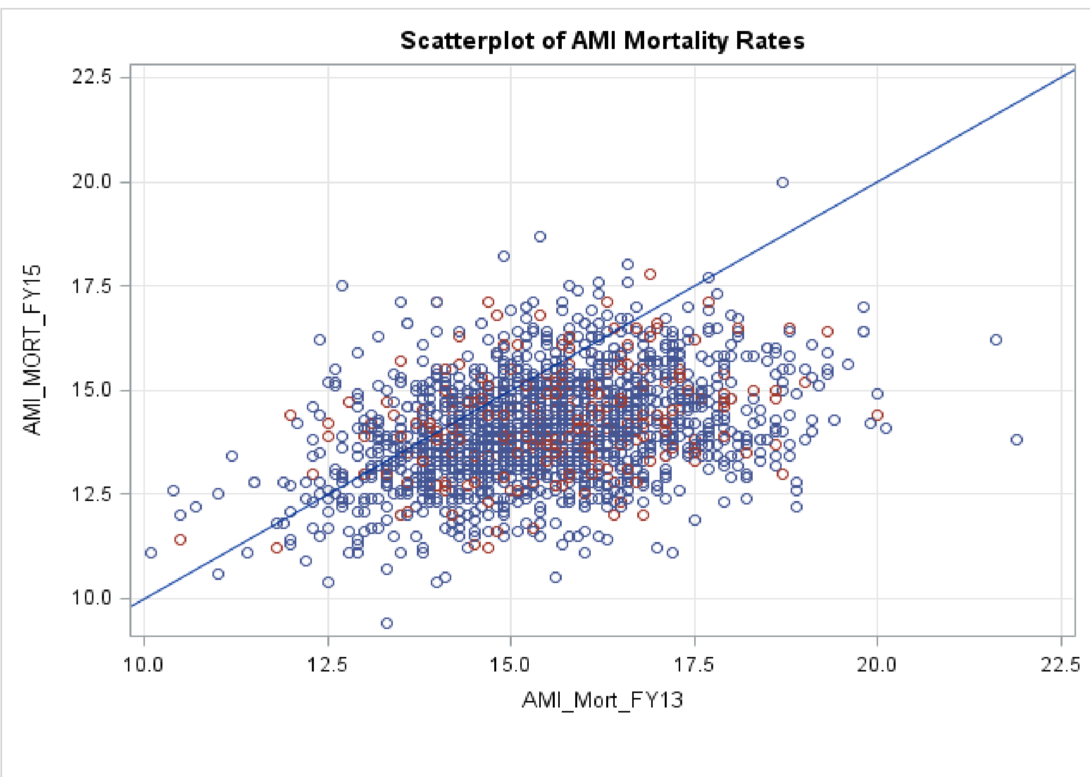

Scatterplot of Heart Failure Readmissions
HF_READ_RATE15
HF_READ_RATE13
15
20
25
30
15
20
25
30


Scatterplot of AMI Readmissions
AMI_READ_RATE15
AMI_READ_RATE13
10
15
20
25
10
15
20
25



Scatterplot of Pneumonia Mortality Rates
PN_MORT_Fy15
25
20
15
10
5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
PN_Mort_FY13


Scatterplot of Heart Failure Mortality Rates
HF_MORT_FY15
HF_Mort_FY13
17.5
15.0
12.5
10.0
7.5
5.0


Scatterplot of AMI Mortality Rates
AMI_MORT_FY15
AMI_Mort_FY13
22.5
20.0
17.5
15.0
12.5
10.0

Appendix B: Pearson Correlation on Covariates and Dependent Variables

	Baseline AMI Readmission Rate	Baseline Heart Failure Readmission Rate	Baseline Pneumonia Readmission Rate	Baseline AMI Mortality Rate	Baseline Heart Failure Morality Rate	Baseline Pneumonia Mortality Rate
Medicare Case Mix	-0.18879*	-0.25827*	-0.09474*	-0.18606*	-0.09218*	-0.11776 *
Total margin	-0.04928*	-0.03499	-0.0491*	-0.04719*	0.02956	-0.04449*
Logarithm of Beds	0.0447	-0.04174*	0.10135*	-0.13927*	-0.13357*	-0.07416 *
Logarithm of Medicare Discharges	0.02174	-0.058*	0.10125*	-0.18338*	-0.10776*	-0.10125*
Rural	0.15136*	0.18896*	0.12904*	-0.03374	-0.13292*	-0.06298*
Medicare Dependent Hospital	0.0253	0.077*	0.02681	0.04381	0.05614*	0.0396*
Sole Community Hospital	-0.08658*	-0.04461*	-0.08999*	0.0751*	0.1232*	0.08602*
For Profit	0.02153	0.07982*	0.04189*	0.09129*	-0.03794	0.03066
Government	0.01831	0.02817	-0.00688	0.08421*	0.04123*	0.0991*

*indicates statistically significant with p-value <0.05.

	Post Period AMI Readmission Rate	Post Period Heart Failure Readmission Rate	Post Period Pneumonia Readmission Rate	Post Period AMI Mortality Rate	Post Period Heart Failure Morality Rate	Post Period Pneumonia Mortality Rate
Medicare Case Mix	-0.16552*	-0.2068*	-0.07377*	-0.13547*	-0.0706*	-0.1003*
Total margin	-0.04992	-0.0354	-0.04513	0.00267	0.01245	-0.0145
Logarithm of Beds	0.08383*	-0.00849	0.12101*	-0.06969*	-0.15751*	-0.06932*
Logarithm of Medicare Discharges	0.05955*	-0.03477	0.10712*	-0.11123*	-0.14416*	-0.05014*
Rural	0.12784*	0.14908*	0.10619*	-0.06084*	-0.12628*	-0.05632*
Medicare Dependent Hospital	0.0077	0.04667*	0.01323	0.08218*	0.06407*	0.05143*
Sole Community Hospital	-0.05306*	-0.03907	-0.06417*	0.03142	0.13002*	0.0847*
For Profit	0.04359	0.06757*	0.04079*	0.04813*	-0.02879	0.00499
Government	0.04609	0.04258*	0.00292	0.07935*	0.04031	0.08175*

*indicates statistically significant with p-value <0.05.

Appendix C: Pearson Correlation of Independent Variables with Covariates and Dependent Variables for the Section 1109 Hospitals

	Section 1109 Payment	Section 1109 Payment Per Bed	Logarithm of Section 1109 Payment	Logarithm of Section 1109 Payment per Bed
Total Margin	-0.0398	-0.0607	-0.0978	0.0910
Logarithm of Medicare Discharges	0.7328 *	0.6531 *	0.9675 *	-0.6499 *
Logarithm of Beds	0.7771 *	0.3701 *	0.8522 *	-0.7798 *
Medicare Case Mix	0.5255 *	0.5499 *	0.5571 *	-0.1359 *
Baseline Pneumonia Discharges for Readmissions Measure	0.7480*	0.5361*	0.7158*	-0.4397 *
Baseline AMI Discharges for Readmissions Measure	0.8620*	0.5961*	0.7436*	-0.3790 *
Baseline Heart Failure Discharges for Readmissions Measure	0.8287*	0.5727*	0.7341*	-0.4237 *
Baseline AMI Readmission Rate	-0.1806 *	-0.1650 *	-0.1841 *	0.1048
Baseline Heart Failure Readmission Rate	-0.1557 *	-0.1971 *	-0.1939 *	0.1277 *
Baseline Pneumonia Readmission Rate	-0.0269	-0.0538	-0.0583	0.0169
Baseline Heart Failure Discharges for Mortality Measure	0.8175 *	0.5602 *	0.7324 *	-0.4302 *
Baseline Pneumonia Discharges for Mortality Measure	0.7377 *	0.5216 *	0.7103 *	-0.4432 *
Baseline AMI Discharges for Mortality Measure	0.8721 *	0.6020 *	0.7746 *	-0.4038 *
Baseline Heart Failure Mortality Rate	-0.0131	0.0059	0.0196	-0.0302
Baseline Pneumonia Mortality Rate	-0.0574	-0.1325	-0.0867	0.0163
Baseline AMI Mortality Rate	-0.2097 *	-0.2074 *	-0.2039 *	0.1315 *
Post Period Pneumonia Discharges for Readmissions Measure	0.8053 *	0.5303 *	0.7651 *	-0.4236 *
Post Period Heart Failure Discharges for Readmissions Measure	0.8633 *	0.5536 *	0.7579 *	-0.3877 *
Post Period AMI Discharges for Readmissions Measure	0.8629 *	0.6127 *	0.7709 *	-0.5731 *
Post Period AMI Readmission Rate	-0.0733	-0.0905	-0.1321 *	0.1220
Post Period Heart Failure Readmission Rate	-0.1624 *	-0.2214 *	-0.2202 *	0.1757 *
Post Period Pneumonia Readmission Rate	-0.0488	-0.1252 *	-0.0646	-0.0122
Post Period AMI Discharges for Mortality Measure	0.8358 *	0.5578 *	0.8005 *	-0.5748 *
Post Period Heart Failure Discharges for Mortality Measure	0.8317 *	0.5226 *	0.7429 *	-0.5808 *
Post Period Pneumonia Discharges for Mortality Measure	0.7094 *	0.4980 *	0.6782 *	-0.5035 *
Post Period AMI Mortality Rate	-0.0798	-0.0920	-0.0690	0.0473
Post Period Heart Failure Mortality Rate	-0.0639	0.0031	0.0164	-0.0375
Post Period Pneumonia Mortality Rate	-0.0831	0.0101	-0.0753	0.0770
Change in AMI Readmission Rate	0.1390 *	0.1046	0.1155	-0.0456
Change in Heart Failure Readmission Rate	-0.0045	-0.0100	-0.0179	0.0450
Change in Pneumonia Readmission Rate	-0.0231	-0.0738	-0.0099	-0.0191
Change in Heart Failure Mortality Rate	-0.0358	-0.0202	-0.0049	-0.0231
Change in Pneumonia Mortality Rate	-0.0347	0.0984	-0.0111	0.0731
Change in AMI Mortality Rate	0.1102	0.0973	0.1052	-0.0545

*indicates statistically significant with p-value <0.05.

Appendix D: Correlations of Dependent Variables

		Baseline AMI Readmission Rate	**Baseline Heart Failure Readmission Rate**	**Baseline Pneumonia Readmission Rate**	**Baseline AMI Mortality Rate**	**Baseline Heart Failure Mortality Rate**	**Baseline Pneumonia Mortality Rate**
Baseline AMI Readmission Rate	Section 1109	1	0.41438*	0.3493*	0.18854*	-0.07897	-0.07885*
	Non-Section 1109	1	0.39502*	0.35418*	0.02589	-0.17588*	-0.04312
Baseline Heart Failure Readmission Rate	Section 1109	0.41438*	1	0.35875*	0.11852*	-0.07947	0.05876
	Non-Section 1109	0.39502*	1	0.45923*	0.01126	-0.11839*	-0.05029 *
Baseline Pneumonia Readmission Rate	Section 1109	0.3493*	0.35875*	1	0.08148	-0.09959	0.01833
	Non-Section 1109	0.35418*	0.45923*	1	-0.00467	-0.15546*	0.04517*
Baseline AMI Mortality Rate	Section 1109	0.18854*	0.11852*	0.08148	1	0.16284*	0.17683*
	Non-Section 1109	0.02589	0.01126	-0.00467	1	0.28467*	0.30837*
Baseline Heart Failure Mortality Rate	Section 1109	-0.07897	-0.07947	-0.09959	0.16284*	1	0.37138*
	Non-Section 1109	-0.17588*	-0.11839*	-0.15546*	0.28467*	1	0.38839*
Baseline Pneumonia Mortality Rate	Section 1109	-0.07885	0.05876	0.01833	0.17683*	0.37138*	1
	Non-Section 1109	-0.04312	-0.05029*	0.04517*	0.30837*	0.38839*	1

*indicates statistically significant with p-value <0.05.

		Post period AMI Readmission Rate	Post period Heart Failure Readmission Rate	Post period Pneumonia Readmission Rate	Post period AMI Mortality Rate	Post period Heart Failure Mortality Rate	Post period Pneumonia Mortality Rate
Post period AMI Readmission Rate	Section 1109	1	0.40767*	0.4147*	0.17638*	-0.1169	0.10036
	Non-Section 1109	1	0.4125*	0.34585*	0.05989*	-0.12918*	0.01026
Post period Heart Failure Readmission Rate	Section 1109	0.40767*	1	0.4385*	0.09861	-0.10185	0.09001
	Non-Section 1109	0.4125*	1	0.46145*	0.04444	-0.08887*	0.00957
Post period Pneumonia Readmission Rate	Section 1109	0.4147*	0.4385*	1	0.13558*	-0.03336	0.02202
	Non-Section 1109	0.34585*	0.46145*	1	0.00257	-0.14567*	0.04832*
Post period AMI Mortality Rate	Section 1109	0.17638*	0.09861	0.13558*	1	0.1411	0.19671
	Non-Section 1109	0.05989*	0.04444	0.00257	1	0.2824*	0.33306*
Post period Heart Failure Mortality Rate	Section 1109	-0.1169	-0.10185	-0.03336	0.1411*	1	0.30613*
	Non-Section 1109	-0.12918*	-0.08887*	-0.14567*	0.2824*	1	0.38796*
Post period Pneumonia Mortality Rate	Section 1109	0.10036	0.09001	0.02202	0.19671*	0.30613*	1
	Non-Section 1109	0.01026	0.00957	0.04832*	0.33306*	0.38796*	1

*indicates statistically significant with p-value <0.05.

		Change in AMI Readmission Rate	Change in Heart Failure Readmission Rate	Change in Pneumonia Readmission Rate	Change in AMI Mortality Rate	Change in Heart Failure Mortality Rate	Change in Pneumonia Mortality Rate
Change in AMI Readmission Rate	Section 1109	1	0.0173	-0.01283	0.05808	-0.04438	-0.05853
	Non-Section 1109	1	0.13141*	0.06885*	0.02906	0.03805	0.04909
Change in Heart Failure Readmission Rate	Section 1109	0.0173	1	0.06949	0.0828	0.00537	0.06889
	Non-Section 1109	0.13141*	1	0.17822*	0.03696	0.07942*	-0.02817
Change in Pneumonia Readmission Rate	Section 1109	-0.01283	0.06949	1	0.01853	0.01794	-0.0331
	Non-Section 1109	0.06885*	0.17822*	1	0.01215	-0.01161	0.05675*
Change in AMI Mortality Rate	Section 1109	0.05808	0.0828	0.01853	1	0.08825	0.09901
	Non-Section 1109	0.02906	0.03696	0.01215	1	0.07327*	0.06179*
Change in Heart Failure Mortality Rate	Section 1109	-0.04438	0.00537	0.01794	0.08825	1	0.11837*
	Non-Section 1109	0.03805	0.07942*	-0.01161	0.07327*	1	0.09265*
Change in Pneumonia Mortality Rate	Section 1109	-0.05853	0.06889	-0.0331	0.09901	0.11837*	1
	Non-Section 1109	0.04909	-0.02817	0.05675*	0.06179*	0.09265*	1

*indicates statistically significant with p-value <0.05.

		Baseline AMI Readmission Rate	Baseline Heart Failure Readmission Rate	Baseline Pneumonia Readmission Rate	Baseline AMI Mortality Rate	Baseline Heart Failure Mortality Rate	Baseline Pneumonia Mortality Rate
Post period AMI Readmission Rate	Section 1109	0.40465*	0.33281*	0.34526*	0.14268	-0.0487	0.08704
	Non-Section 1109	0.31898*	0.34037*	0.2532*	0.04395	-0.12412*	0.01393
Post period Heart Failure Readmission Rate	Section 1109	0.48029*	0.45988*	0.43165*	0.06114	-0.03701	0.09636
	Non-Section 1109	0.31598*	0.39546*	0.34357*	0.02691	-0.10878*	0.04277
Post period Pneumonia Readmission Rate	Section 1109	0.38522*	0.29921*	0.39996*	0.03538*	0.00645*	0.08*
	Non-Section 1109	0.3311*	0.35741*	0.40803*	-0.0223	-0.13214*	0.03374
Post period AMI Mortality Rate	Section 1109	0.14296*	0.07628	0.14312*	0.30231	0.18925	0.16542
	Non-Section 1109	0.00082	-0.03438	0.0007	0.35905*	0.26424*	0.26682*
Post period Heart Failure Mortality Rate	Section 1109	-0.0959	-0.14532*	-0.177*	0.01608	0.26402*	0.15323*
	Non-Section 1109	-0.22602*	-0.20251*	-0.15535*	0.23881*	0.41751*	0.27927*
Post period Pneumonia Mortality Rate	Section 1109	0.01421	-0.00913	0.00483	0.06071	0.31604*	0.31003*
	Non-Section 1109	-0.07627*	-0.03922	-0.00634	0.27046*	0.38187*	0.44092*

*indicates statistically significant with p-value <0.05

Appendix E: Other Multivariate Linear Regression Models for Hypothesis 3

Table 26A Multiple Linear Regression Model with Change in 30-Day AMI Readmission Rate as a dependent variable and Section 1109 payment amount as the independent variable.

	Unstandardized Coefficients	**T-Value**	**P-Value**
(Constant)	16.0323	7.3000	<.0001
Baseline Readmission Rate for AMI	-0.0017	-2.3500	0.0196
Baseline Discharges for AMI	-0.8135	-19.3600	<.0001
Medicare Case Mix	-0.9655	-2.1400	0.0335
Total Margin	-0.0041	-0.5700	0.5680
Logarithm of Bed Count	-0.4171	-1.6000	0.1122
Logarithm of Medicare Discharges	-0.0360	-0.1400	0.8914
Rural	-0.0357	-0.1800	0.8612
Medicare Dependent Hospital Status	-0.1697	-0.4900	0.6232
Sole Community Hospital Status	0.1245	0.5900	0.5539
For Profit Ownership	0.7710	3.1600	0.0018
Government Ownership	-0.0125	-0.0500	0.9632
Section 1109 Payment	0.0000	3.1000	0.0022
Number of Observations	215		
F-value	38.6000		<.0001
R-squared	0.6963		
R-squared(adj)	0.6783		
Durbin-Watson Coefficient	2.017		

Table 26B Multiple Linear Regression Model with Change in 30-Day Heart Failure Readmission Rate as a dependent variable and Section 1109 payment amount as the independent variable.

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	14.1643	3.98	<.0001
Baseline Readmission Rate for Heart Failure	-0.0004	-0.48	0.6289
Baseline Discharges for Heart Failure	-0.5597	-9.13	<.0001
Case Mix	-1.8679	-2.41	0.0168
Total Margin	-0.0044	-0.39	0.6940
Logarithm of Bed Count	0.4352	1.05	0.2959
Logarithm of Medicare Discharges	-0.3745	-0.8	0.4270
Rural	-0.1684	-0.52	0.6024
Medicare Dependent Hospital Status	1.2792	2.31	0.0218
Sole Community Hospital Status	0.0448	0.13	0.8931
For Profit Ownership	0.2405	0.61	0.5433
Government Ownership	0.3268	0.77	0.4424
Section 1109 Payment	0.0000	0.8	0.4270
Number of Observations	215		
F-value	8.78		<.0001
R-squared	0.3428		
R-squared(adj)	0.3037		
Durbin-Watson Coefficient	2.056		

Table 26C Multiple Linear Regression Model with Change in 30-Day Pneumonia Readmission Rate as a dependent variable and Section 1109 payment amount as the independent variable.

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	9.1042	2.88	0.0044
Baseline Discharges for Pneumonia	0.0014	1.48	0.1393
Baseline Readmission Rate for Pneumonia	-0.5641	-7.9	<.0001
Case Mix	-0.9697	-1.44	0.1503
Total Margin	-0.0052	-0.51	0.6078
Logarithm of Bed Count	0.7976	2.2	0.0293
Logarithm of Medicare Discharges	-0.3607	-0.89	0.3733
Rural	-0.1614	-0.56	0.5757
Medicare Dependent Hospital Status	0.9390	1.93	0.0556
Sole Community Hospital Status	0.0301	0.1	0.9191
For Profit Ownership	-0.0355	-0.1	0.9194
Government Ownership	0.1137	0.3	0.7640
Section 1109 Payment	0.0000	-1.37	0.1708
Number of Observations	215		
F-value	6.92		<.0001
R-squared	0.2912		
R-squared(adj)	0.2491		
Durbin-Watson Coefficient	1.725		

Table 26D Multiple Linear Regression Model with Change in 30-Day Heart Failure Mortality Rate as a dependent variable and Section 1109 payment amount as the independent variable.

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	5.1215	1.88	0.0619
Baseline Discharges for Heart Failure	-0.0007	-0.85	0.3967
Baseline Mortality Rate for Heart Failure	-0.7724	-13.07	<.0001
Case Mix	0.1581	0.26	0.7987
Total Margin	0.0034	0.36	0.7156
Logarithm of Bed Count	0.1917	0.55	0.5812
Logarithm of Medicare Discharges	0.5968	1.52	0.1293
Rural	-0.0751	-0.28	0.7814
Medicare Dependent Hospital Status	0.2325	0.51	0.6137
Sole Community Hospital Status	-0.1563	-0.56	0.5746
For Profit Ownership	-0.3703	-1.14	0.2557
Government Ownership	-0.9363	-2.62	0.0093
Section 1109 Payment	0.0000	-2.11	0.0362
Number of Observations	215		
F-value	16.97		<.0001
R-squared	0.5020		
R-squared(adj)	0.4724		
Durbin-Watson Coefficient	2.086		

Table 26E Multiple Linear Regression Model with Change in 30-Day Pneumonia Mortality Rate as a dependent variable and Section 1109 payment amount as the independent variable.

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	11.6847	2.98	0.0033
Baseline Discharges for Pneumonia	-0.0001	-0.11	0.9096
Baseline Mortality Rate for Pneumonia	-0.6134	-7.88	<.0001
Case Mix	0.3845	0.44	0.6621
Total Margin	-0.0029	-0.22	0.8264
Logarithm of Bed Count	-0.9843	-2.03	0.0440
Logarithm of Medicare Discharges	0.6064	1.12	0.2625
Rural	-0.0593	-0.16	0.8770
Medicare Dependent Hospital Status	-0.2342	-0.36	0.7199
Sole Community Hospital Status	0.0036	0.01	0.9928
For Profit Ownership	0.4696	1.02	0.3086
Government Ownership	-0.2675	-0.52	0.6016
Section 1109 Payment	0.0000	0.01	0.9925
Number of Observations	215		
F-value	6.6		<.0001
R-squared	0.2817		
R-squared(adj)	0.2390		
Durbin-Watson Coefficient	2.038		

Table 26F Multiple Linear Regression Model with Change in 30-Day AMI Mortality Rate as a dependent variable and Section 1109 payment amount as the independent variable.

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	7.8521	3.11	0.0021
Baseline Discharges for AMI	-0.0017	-1.63	0.1047
Baseline Mortality Rate for AMI	-0.7815	-13.43	<.0001
Case Mix	-0.5340	-1.07	0.2874
Total Margin	-0.0108	-1.29	0.1974
Logarithm of Bed Count	0.0830	0.27	0.7900
Logarithm of Medicare Discharges	0.4636	1.44	0.1525
Rural	-0.1529	-0.63	0.5313
Medicare Dependent Hospital Status	0.7686	1.86	0.0650
Sole Community Hospital Status	0.1700	0.68	0.4996
For Profit Ownership	0.0679	0.23	0.8173
Government Ownership	-0.0705	-0.22	0.8274
Section 1109 Payment	0.0000	0.03	0.9728
Number of Observations	215		
F-value	17.31		<.0001
R-squared	0.5070		
R-squared(adj)	0.4777		
Durbin-Watson Coefficient	1.883		

Table 27A Multiple Linear Regression Model with Change in 30-Day AMI Readmission Rate as a dependent variable and Section 1109 payment per bed as the independent variable.

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	13.3822	6.71	<.0001
Baseline Readmission Rate for AMI	-0.0007	-1.15	0.2522
Baseline Discharges for AMI	-0.8101	-18.84	<.0001
Case Mix	-1.1870	-2.15	0.0330
Total Margin	-0.0014	-0.2	0.8411
Logarithm of Bed Count	0.4533	1.12	0.2636
Logarithm of Medicare Discharges	-0.2537	-0.65	0.5141
Rural	-0.0063	-0.03	0.9760
Medicare Dependent Hospital Status	0.0239	0.07	0.9448
Sole Community Hospital Status	0.1216	0.57	0.5716
For Profit Ownership	0.7544	3.04	0.0027
Government Ownership	0.1753	0.66	0.5077
Section 1109 Payment	0.0001	1.63	0.1055
Number of Observations	215		
F-value	36.77		<.0001
R-squared	0.6860		
R-squared(adj)	0.6673		
Durbin-Watson Coefficient	2.025		

Table 27B Multiple Linear Regression Model with Change in 30-Day Heart Failure Readmission Rate as a dependent variable and Section 1109 payment per bed as the independent variable.

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	12.7602	4.07	<.0001
Baseline Readmission Rate for Heart Failure	-0.0002	-0.2	0.8448
Baseline Discharges for Heart Failure	-0.5550	-9.08	<.0001
Case Mix	-1.7502	-1.98	0.0489
Total Margin	-0.0034	-0.3	0.7630
Logarithm of Bed Count	0.6866	1.11	0.2681
Logarithm of Medicare Discharges	-0.3936	-0.61	0.5413
Rural	-0.1633	-0.5	0.6153
Medicare Dependent Hospital Status	1.3749	2.55	0.0116
Sole Community Hospital Status	0.0589	0.18	0.8606
For Profit Ownership	0.2220	0.56	0.5750
Government Ownership	0.3967	0.95	0.3417
Section 1109 Payment	0.0000	0.22	0.8229
Number of Observations	215		
F-value	8.71		<.0001
R-squared	0.3409		
R-squared(adj)	0.3017		
Durbin-Watson Coefficient	2.067		

Table 27C Multiple Linear Regression Model with Change in 30-Day Pneumonia Readmission Rate as a dependent variable and Section 1109 payment per bed as the independent variable.

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	11.6725	4.4	<.0001
Baseline Cases for Pneumonia	0.0011	1.18	0.2402
Baseline Readmission Rate for Pneumonia	-0.5757	-8.07	<.0001
Case Mix	-1.1321	-1.46	0.1461
Total Margin	-0.0064	-0.63	0.5274
Logarithm of Bed Count	0.4604	0.83	0.4057
Logarithm of Medicare Discharges	-0.4216	-0.74	0.4602
Rural	-0.1687	-0.58	0.5614
Medicare Dependent Hospital Status	0.7904	1.66	0.0991
Sole Community Hospital Status	0.0213	0.07	0.9433
For Profit Ownership	-0.0086	-0.02	0.9804
Government Ownership	0.0047	0.01	0.9899
Section 1109 Payment	0.0000	-0.32	0.7455
Number of Observations	215		
F-value	6.71		<.0001
R-squared	0.2849		
R-squared(adj)	0.2425		
Durbin-Watson Coefficient	1.72		

Table 27D Multiple Linear Regression Model with Change in 30-Day Heart Failure Mortality Rate as a dependent variable and Section 1109 payment per bed as the independent variable.

	Unstandardized Coefficients	**T-Value**	**P-Value**
(Constant)	8.7596	3.62	0.0004
Baseline Cases for Heart Failure	-0.0014	-1.78	0.0767
Baseline Mortality Rate for Heart Failure	-0.7704	-12.9	<.0001
Case Mix	-0.3642	-0.51	0.6133
Total Margin	0.0017	0.18	0.8607
Logarithm of Bed Count	-0.0677	-0.13	0.8974
Logarithm of Medicare Discharges	0.3485	0.64	0.5236
Rural	-0.0744	-0.27	0.7865
Medicare Dependent Hospital Status	0.0148	0.03	0.9740
Sole Community Hospital Status	-0.2046	-0.73	0.4691
For Profit Ownership	-0.3300	-1	0.3162
Government Ownership	-1.1365	-3.23	0.0014
Section 1109 Payment	0.0000	0.1	0.9176
Number of Observations	215		
F-value	16.24		<.0001
R-squared	0.4910		
R-squared(adj)	0.4608		
Durbin-Watson Coefficient	2.11		

Table 27E Multiple Linear Regression Model with Change in 30-Day Pneumonia Mortality Rate as a dependent variable and Section 1109 payment amount as the independent variable.

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	13.1837	4	<.0001
Baseline Discharges for Pneumonia	-0.0002	-0.16	0.8764
Baseline Mortality Rate for Pneumonia	-0.6179	-7.94	<.0001
Case Mix	-0.1318	-0.13	0.8966
Total Margin	-0.0026	-0.2	0.8439
Logarithm of Bed Count	-0.4571	-0.62	0.5351
Logarithm of Medicare Discharges	0.0953	0.13	0.9000
Rural	-0.0293	-0.08	0.9390
Medicare Dependent Hospital Status	-0.2703	-0.43	0.6699
Sole Community Hospital Status	-0.0385	-0.1	0.9225
For Profit Ownership	0.4970	1.08	0.2806
Government Ownership	-0.3176	-0.63	0.5275
Section 1109 Payment	0.0001	0.9	0.3690
Number of Observations	215		
F-value	6.7		<.0001
R-squared	0.2846		
R-squared(adj)	0.2421		
Durbin-Watson Coefficient	2.033		

Table 27F Multiple Linear Regression Model with Change in 30-Day AMI Mortality Rate as a dependent variable and Section 1109 payment per bed as the independent variable.

	Unstandardized Coefficients	T-Value	P-Value
(Constant)	8.5260	3.8	0.0002
Baseline Discharges for AMI	-0.0018	-1.98	0.0487
Baseline Mortality Rate for AMI	-0.7854	-13.49	<.0001
Case Mix	-0.8121	-1.35	0.1784
Total Margin	-0.0107	-1.29	0.1990
Logarithm of Bed Count	0.3832	0.81	0.4184
Logarithm of Medicare Discharges	0.1993	0.43	0.6659
Rural	-0.1353	-0.55	0.5805
Medicare Dependent Hospital Status	0.7555	1.87	0.0628
Sole Community Hospital Status	0.1469	0.58	0.5609
For Profit Ownership	0.0829	0.28	0.7779
Government Ownership	-0.1071	-0.34	0.7315
Section 1109 Payment	0.0001	0.78	0.4349
Number of Observations	215		
F-value	17.41		<.0001
R-squared	0.5085		
R-squared(adj)	0.4793		
Durbin-Watson Coefficient	1.877		

Appendix F: Other Difference in Differences Models for Hypothesis 3

Table 28A Difference in Differences Model with Change in 30-Day AMI Mortality Rate as a dependent variable.

	Independent Variable is Amount of Section 1109 Payment			Independent Variable is Logarithm of Section 1109 Payment			Independent Variable is Section 1109 Payment Per Bed		
	Unstandardized Coefficients	T-Value	P-Value	Unstandardized Coefficients	T-Value	P-Value	Unstandardized Coefficients	T-Value	P-Value
(Constant)	15.0079	27.3100	<.0001	15.1168	27.3500	<.0001	15.0392	27.27	<.0001
Baseline Discharges for AMI	-0.0022	-7.3600	<.0001	-0.0022	-7.2800	<.0001	-0.0021	-7.18	<.0001
Medicare Case Mix	-0.6452	-3.9700	<.0001	-0.6582	-4.0500	<.0001	-0.6807	-4.16	<.0001
Total Margin	-0.0024	-2.2200	0.0263	-0.0024	-2.2200	0.0266	-0.0024	-2.21	0.027
Logarithm of Bed Count	0.2186	2.3300	0.0200	0.2263	2.4100	0.0159	0.2679	2.80	0.005
Logarithm of Medicare Discharges	0.0653	0.6600	0.5103	0.0480	0.4800	0.6289	0.0343	0.34	0.732
Rural	0.3355	3.4800	0.0005	0.3367	3.4900	0.0005	0.3337	3.46	6E-04
Medicare Dependent Hospital Status	-0.0874	-0.5700	0.5683	-0.0855	-0.5600	0.5767	-0.0821	-0.54	0.592
Sole Community Hospital Status	-0.0855	-0.8000	0.4220	-0.0858	-0.8100	0.4203	-0.0885	-0.83	0.406
For Profit Ownership	0.3886	4.6500	<.0001	0.3877	4.6400	<.0001	0.3907	4.67	<.0001
Government Ownership	0.2885	3.2200	0.0013	0.2909	3.2500	0.0012	0.2945	3.29	0.001
Section 1109 Hospital Status	0.2153	2.3100	0.0209	0.2128	2.2900	0.0223	0.2220	2.38	0.017
Difference-in-Difference	0.0000	2.4100	0.0162	0.2921	2.5900	0.0097	0.0001	1.85	0.064
Year	-1.6173	-10.1100	<.0001	-5.3977	-3.4500	0.0006	-1.8513	-6.39	<.0001
Number of Observations	2186								
F-value	30.90		<.0001	30.98		<.0001	30.69		<.0001
R-squared	0.1561			0.1564			0.1552		
R-squared(adj)	0.1510			0.1514			0.1501		
Durbin-Watson	1.881			1.883			1.881		

Table 28B Difference in Difference Model with Change in 30-Day Heart Failure Mortality Rate as a dependent variable.

	Independent Variable is Amount of Section 1109 Payment			Independent Variable is Logarithm of Section 1109 Payment			Independent Variable is Section 1109 Payment Per Bed		
	Unstandardized Coefficients	T-Value	P-Value	Unstandardized Coefficients	T-Value	P-Value	Unstandardized Coefficients	T-Value	P-Value
(Constant)	10.4132	24.6400	<.0001	10.5413	24.4800	<.0001	10.4033	24.32	<.0001
Baseline Discharges for Heart Failure	-0.0012	-5.5900	<.0001	-0.0012	-5.4600	<.0001	-0.0012	-5.51	<.0001
Medicare Case Mix	-0.1494	-0.9300	0.3531	-0.1533	-0.9500	0.3403	-0.1521	-0.94	0.347
Total Margin	0.0020	1.6800	0.0922	0.0020	1.7000	0.0900	0.0020	1.68	0.092
Logarithm of Bed Count	-0.2411	-2.7400	0.0062	-0.2347	-2.6700	0.0076	-0.2289	-2.55	0.011
Logarithm of Medicare Discharges	0.3673	4.1000	<.0001	0.3459	3.8300	0.0001	0.3604	3.94	<.0001
Rural	0.2175	2.3900	0.0169	0.2219	2.4400	0.0147	0.2151	2.36	0.018
Medicare Dependent Hospital Status	0.0967	0.7200	0.4726	0.0936	0.7000	0.4866	0.0992	0.74	0.461
Sole Community Hospital Status	0.0249	0.2500	0.8011	0.0230	0.2300	0.8160	0.0249	0.25	0.801
For Profit Ownership	-0.1381	-1.7000	0.0888	-0.1378	-1.7000	0.0894	-0.1368	-1.69	0.092
Government Ownership	0.0293	0.3500	0.7264	0.0292	0.3500	0.7268	0.0330	0.39	0.693
Section 1109 Hospital Status	0.7051	7.7400	<.0001	0.7030	7.7200	<.0001	0.7084	7.78	<.0001
Difference-in-Difference	0.0000	1.0500	0.2923	0.1624	1.8700	0.0620	0.0000	0.49	0.622
Year	0.3787	2.6500	0.0080	-1.7162	-1.4600	0.1442	0.3620	1.50	0.134
Number of Observations	2709			2709			2709		
F-value	26.21		<.0001	26.42		<.0001	26.14		<.0001
R-squared	0.1122			0.1130			0.1120		
R-squared(adj)	0.1080			0.1087			0.1077		
Durbin-Watson	1.837			1.839			1.835		

Table 28C Difference in Difference Model with Change in 30-Day Pneumonia Mortality Rate as a dependent variable.

	Independent Variable is Amount of Section 1109 Payment			Independent Variable is Logarithm of Section 1109 Payment			Independent Variable is Section 1109 Payment Per Bed		
	Unstandardized Coefficients	T-Value	P-Value	Unstandardized Coefficients	T-Value	P-Value	Unstandardized Coefficients	T-Value	P-Value
(Constant)	12.7778	28.6900	<.0001	12.7998	28.44	<.0001	18.6826	28.47	<.0001
Baseline Discharges for Pneumonia	0.0001	0.4900	0.6268	0.0001	0.37	0.7126	-0.0012	-4.34	<.0001
Medicare Case Mix	-0.5566	-2.6700	0.0076	-0.5668	-2.72	0.0065	-1.8728	-9.80	<.0001
Total Margin	-0.0027	-1.9000	0.0575	-0.0027	-1.89	0.0585	-0.0030	-2.41	0.016
Logarithm of Bed Count	0.2252	2.1600	0.0312	0.2237	2.14	0.0322	0.4206	3.82	1E-04
Logarithm of Medicare Discharges	-0.1750	-1.7000	0.0888	-0.1737	-1.69	0.0913	0.1799	1.62	0.106
Rural	0.2825	2.6100	0.0091	0.2864	2.65	0.0082	-0.1338	-1.16	0.248
Medicare Dependent Hospital Status	-0.0100	-0.0600	0.9503	-0.0129	-0.08	0.9361	0.1802	0.93	0.35
Sole Community Hospital Status	-0.0808	-0.6900	0.4911	-0.0820	-0.70	0.4846	-0.2247	-1.74	0.082
For Profit Ownership	0.3047	3.1500	0.0017	0.3032	3.13	0.0018	0.1986	2.02	0.043
Government Ownership	0.4203	4.2200	<.0001	0.4170	4.19	<.0001	0.0791	0.73	0.467
Section 1109 Hospital Status	0.4481	4.1300	<.0001	0.4459	4.11	<.0001	-0.6543	-5.93	<.0001
Difference-in-Difference	0.0000	-0.4500	0.6493	0.0162	0.16	0.8717	0.0000	1.06	0.29
Year	4.4837	26.6300	<.0001	4.2252	3.14	0.0017	-2.6550	-7.62	<.0001
Number of Observations	2736			2736			1939		
F-value	169.05		<.0001	169.02		<.0001	81.47		<.0001
R-squared	0.4467			0.4467			0.3549		
R-squared(adj)	0.4441			0.4440			0.3506		
Durbin-Watson	1.877			1.878			1.81		

Table 28D Difference in Difference Model with Change in 30-Day AMI Readmission Rate as a dependent variable.

	Independent Variable is Amount of Section 1109 Payment			Independent Variable is Logarithm of Section 1109 Payment			Independent Variable is Section 1109 Payment Per Bed		
	Unstandardized Coefficients	T-Value	P-Value	Unstandardized Coefficients	T-Value	P-Value	Unstandardized Coefficients	T-Value	P-Value
(Constant)	18.5854	28.29	<.0001	18.5133	27.97	<.0001	17.1048	50.58	<.0001
Baseline Discharges for AMI	-0.0012	-4.24	<.0001	-0.0012	-4.24	<.0001	-0.0007	-3.54	0.0004
Medicare Case Mix	-1.8500	-9.74	<.0001	-1.8445	-9.70	<.0001	-2.1117	-13.66	<.0001
Total Margin	-0.0030	-2.42	0.0158	-0.0030	-2.42	0.0157	-0.0025	-2.38	0.0173
Logarithm of Bed Count	0.3984	3.69	0.0002	0.3998	3.71	0.0002	0.2625	3.37	0.0008
Logarithm of Medicare Discharges	0.2014	1.83	0.0667	0.2082	1.89	0.0586	0.4480	5.86	<.0001
Rural	-0.1401	-1.21	0.2265	-0.1435	-1.24	0.2156	-0.1342	-1.65	0.0996
Medicare Dependent Hospital Status	0.1780	0.92	0.3561	0.1768	0.92	0.3594	0.1398	1.15	0.2484
Sole Community Hospital Status	-0.2222	-1.72	0.0858	-0.2220	-1.72	0.0860	-0.1245	-1.40	0.1607
For Profit Ownership	0.2003	2.04	0.0414	0.2017	2.06	0.0400	0.2102	2.88	0.0040
Government Ownership	0.0856	0.79	0.4311	0.0877	0.81	0.4196	0.0290	0.39	0.6994
Section 1109 Hospital Status	-0.6529	-5.92	<.0001	-0.6501	-5.89	<.0001	-0.5018	-6.13	<.0001
Difference-in-Difference	0.0000	-0.28	0.7803	-0.1179	-0.84	0.3987	-0.0001	-1.89	0.0587
Year	-2.2811	-11.86	<.0001	-0.6747	-0.35	0.7295	-0.8149	-3.74	0.0002
Number of Observations	1939			1939			2749		
F-value	81.34		<.0001	81.42		<.0001	67.71		<.0001
R-squared	0.3546			0.3548			0.2435		
R-squared(adj)	0.3502			0.3504			0.2399		
Durbin-Watson	1.809			1.809			1.748		

Table 28E Difference in Difference Model with Change in 30-Day Pneumonia Readmission Rate as a dependent variable.

	Independent Variable is Amount of Section 1109 Payment			Independent Variable is Logarithm of Section 1109 Payment			Independent Variable is Section 1109 Payment Per Bed		
	Unstandardized Coefficients	T-Value	P-Value	Unstandardized Coefficients	T-Value	P-Value	Unstandardized Coefficients	T-Value	P-Value
(Constant)	17.1724	51.0	<.0001	17.1097	50.62	<.0001	17.1048	50.58	<.0001
Baseline Discharges for Pneumonia	-0.0007	-3.30	0.0010	-0.0007	-3.40	0.0007	-0.0007	-3.54	0.0004
Medicare Case Mix	-2.1252	-13.78	<.0001	-2.1190	-13.75	<.0001	-2.1117	-13.66	<.0001
Total Margin	-0.0025	-2.37	0.0177	-0.0025	-2.39	0.0169	-0.0025	-2.38	0.0173
Logarithm of Bed Count	0.2941	3.84	0.0001	0.2869	3.75	0.0002	0.2625	3.37	0.0008
Logarithm of Medicare Discharges	0.4201	5.52	<.0001	0.4321	5.69	<.0001	0.4480	5.86	<.0001
Rural	-0.1318	-1.62	0.1059	-0.1340	-1.64	0.1003	-0.1342	-1.65	0.0996
Medicare Dependent Hospital Status	0.1385	1.14	0.2528	0.1411	1.17	0.2439	0.1398	1.15	0.2484
Sole Community Hospital Status	-0.1303	-1.47	0.1421	-0.1286	-1.45	0.1473	-0.1245	-1.40	0.1607
For Profit Ownership	0.2136	2.93	0.0035	0.2139	2.93	0.0034	0.2102	2.88	0.0040
Government Ownership	0.0316	0.42	0.6739	0.0302	0.40	0.6875	0.0290	0.39	0.6994
Section 1109 Hospital Status	-0.4993	-6.09	<.0001	-0.4981	-6.08	<.0001	-0.5018	-6.13	<.0001
Difference-in-Difference	0.0000	-1.37	0.1693	-0.1406	-1.84	0.0662	-0.0001	-1.89	0.0587
Year	-1.0778	-8.46	<.0001	0.7013	0.68	0.4946	-0.8149	-3.74	0.0002
Number of Observations	2749			2749			2749		
F-value	67.54		<.0001	67.69		<.0001	67.71		<.0001
R-squared	0.2430			0.2434			0.2435		
R-squared(adj)	0.2394			0.2398			0.2399		
Durbin-Watson	1.749			1.75			1.748		

Table 28F Difference in Difference Model with Change in 30-Day Heart Failure Readmission Rate as a dependent variable.

	Independent Variable is Amount of Section 1109 Payment			Independent Variable is Logarithm of Section 1109 Payment			Independent Variable is Section 1109 Payment Per Bed		
	Unstandardized Coefficients	T-Value	P-Value	Unstandardized Coefficients	T-Value	P-Value	Unstandardized Coefficients	T-Value	P-Value
(Constant)	25.2451	52.6500	<.0001	25.1481	51.73	<.0001	25.2251	52.20	<.0001
Baseline Discharges for Heart Failure	-0.0003	-1.2200	0.2230	-0.0003	-1.34	0.1806	-0.0003	-1.32	0.1868
Medicare Case Mix	-3.0255	-16.4000	<.0001	-3.0198	-16.37	<.0001	-3.0139	-16.26	<.0001
Total Margin	-0.0020	-1.4400	0.1499	-0.0020	-1.44	0.1487	-0.0020	-1.44	0.1490
Logarithm of Bed Count	0.4444	4.5000	<.0001	0.4394	4.45	<.0001	0.4226	4.21	<.0001
Logarithm of Medicare Discharges	0.2067	2.0800	0.0372	0.2228	2.23	0.0257	0.2222	2.20	0.0278
Rural	0.1325	1.2600	0.2074	0.1289	1.23	0.2198	0.1328	1.26	0.2064
Medicare Dependent Hospital Status	0.1116	0.7200	0.4724	0.1133	0.73	0.4655	0.1102	0.71	0.4778
Sole Community Hospital Status	-0.3052	-2.6700	0.0076	-0.3030	-2.65	0.0080	-0.3029	-2.65	0.0081
For Profit Ownership	0.3913	4.1900	<.0001	0.3908	4.18	<.0001	0.3897	4.17	<.0001
Government Ownership	0.1118	1.1600	0.2468	0.1101	1.14	0.2532	0.1080	1.12	0.2624
Section 1109 Hospital Status	-1.0018	-9.4900	<.0001	-1.0010	-9.49	<.0001	-1.0057	-9.54	<.0001
Difference-in-Difference	0.0000	-1.1000	0.2727	-0.1647	-1.60	0.1107	0.0000	-0.95	0.3403
Year	-2.1950	-13.2300	<.0001	-0.0842	-0.06	0.9519	-2.0668	-7.37	<.0001
Number of Observations	2728			2728			2728		
F-value	118.72		<.0001	118.88		<.0001	118.68		<.0001
R-squared	0.3625			0.3628			0.3624		
R-squared(adj)	0.3595			0.3598			0.3594		
Durbin-Watson	1.736			1.737			1.737		

Appendix G: Resume

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EDUCATION

May 2018(expected) **Johns Hopkins Bloomberg School of Public Health**, Baltimore, MD
Candidate for Doctorate in Public Health in Health Leadership & Management

May 2007 **Johns Hopkins Bloomberg School of Public Health,** Baltimore, MD
Masters in Health Science in Health Policy
Certificate in Health Finance & Management

May 2005 **Tufts University**, Medford, MA
Bachelor of Arts in Political Science & Community Health

PROFESSIONAL EXPERIENCE

9/2014-present **Centers for Medicare and Medicaid Services**, Baltimore, MD*, Senior Technical Advisor: Health Insurance Specialist*

- Payment policy expert in the State Innovations Group in the Center for Medicare and Medicaid Innovations(CMMI) with expertise in Medicare payment policy and Affordable Care Act provisions
- Led the design, state negotiations and implementation of the Pennsylvania Rural Health Model, a hospital global budget model for rural hospitals in Pennsylvania
- Developed the Comprehensive Care Joint Replacement bundled payments model through rulemaking, conducting data analysis to inform development of model, drafting the impacts analysis for rulemaking
- Develops the policies and process for Medicare participation in State Innovations Model where States are awarded grants from CMMI to design and implement multi-payer health care payment delivery reform
- Led quality measurement and improvement efforts in all-payer statewide payment models, including in the Maryland All-Payer Model and the Vermont All Payer ACO Model
- Recipient of several agency awards related to development of the Comprehensive Care Join Replacement Model and All-Payer Models

9/2006- 9/2014 **Centers for Medicare and Medicaid Services**, Baltimore, MD*, Technical Advisor: Health Insurance Specialist*

- Payment policy expert in the Division of Acute Care, which publishes regulations annually to establish the Medicare payment rates for inpatient hospital services for acute care and long term care hospitals. These policies account for Medicare payments of $120 billion per year to acute care and long term care hospitals.
- Implemented several provisions under the Affordable Care Act, including the Medicare Hospital Readmissions Reduction Program, a $300 million provision to reduce payments to hospitals that perform poorly on readmissions, and the Medicare Disproportionate Share Hospital Payment policy, a $10 billion payment policy that provides that additional payments to hospitals for treating low-income and indigent patients
- Performed payment impact modeling using SAS and Excel, forecasting how policy changes will impact Medicare hospital payments to different types of hospitals, and monitoring the accuracy of Medicare hospital payments, to inform decision making
- Provided advice through oral and written policy briefings to CMS leadership on Medicare payment policies and provides detailed and thoughtful technical health policy analyses to inform decision making on politically sensitive issues
- Represented the agency in presentations to external groups, such as hospital organizations, private industry and State and local government agencies on health policy issues
- Provided technical assistance on payment forecasting and in support of legislative proposals to the Congressional Budget Office, the Office of Management and Budget, Medicare Payment Advisory Commission (MedPAC) and CMS Office of Legislation

- Certified as a Contracting Officer Representative, managing two contracts worth $500,000 related to implementation of provisions under the Affordable Care Act
- Recipient of several agency awards related to the Medicare payment policy work including the Administrator's Achievement Award for assistance in development of the Affordable Care Act and the Administrator's Citation for Distinguished Service for revising the inpatient hospital payment policy

9/2012- 1/2013 **Centers for Disease Control and Prevention (CDC)**, Harare, Zimbabwe, *Fellow*

- Fellow in the International Experience and Technical Assistance Program, a highly selective program where chosen applicants are on detail to an international office for the Centers for Disease Control and Prevention
- Organized the Country Management & Support site visit, an annual program audit conducted by CDC Headquarters, where tasks included preparing presentations and program documentation for the visit, and implemented program and management recommendations provided during the site visit
- Developed a policy case-study in collaboration with the Zimbabwean government, and presented findings to the U.S Office of Global AIDS Coordinator on Zimbabwe's National AIDS Levy, an income tax to support HIV/ AIDS programs in Zimbabwe. Conducted documentation review and key informant interviews with the Zimbabwean government, international organizations, including UNAIDS and USAID, and Zimbabwean civil society stakeholders
- Liaised with high-level officials from CDC Headquarters, the U.S Embassy, and the Ministry of Health in preparation for the Country Management & Support visit

1/2006- 4/2006 **Cecil County Health Department** Elkton, MD, *Consultant*

- Wrote a federal grant proposal and needs assessment that was submitted to the Health Resources and Services Administration to receive funding to establish a primary health care facility in the medically underserved Cecil County, Maryland, which led to the award of $733,333 to the West Cecil Community Center. Conducted interviews with the medically underserved population to formulate the grant proposal.

SKILLS & TRAININGS

Computer: Proficient in SAS, Microsoft Word, Excel, and PowerPoint software
Trainings: Contracting Officer Representative Training, Centers for Medicare and Medicaid Services, May 2011; Preparing for Work Overseas, Centers for Disease Control and Prevention, March 2012

PUBLICATIONS

Bhat, Nisha, et al. "Zimbabwe's national AIDS levy: A case study." SAHARA-J: Journal of Social Aspects of HIV/AIDS 13.1 (2016): 1-7.